

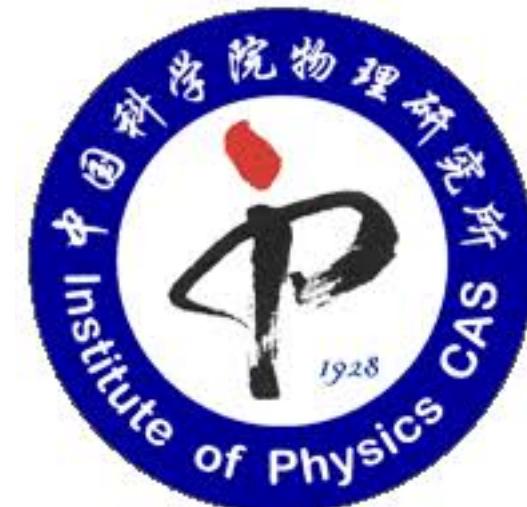
# Born Machines

## A fresh approach to quantum machine learning

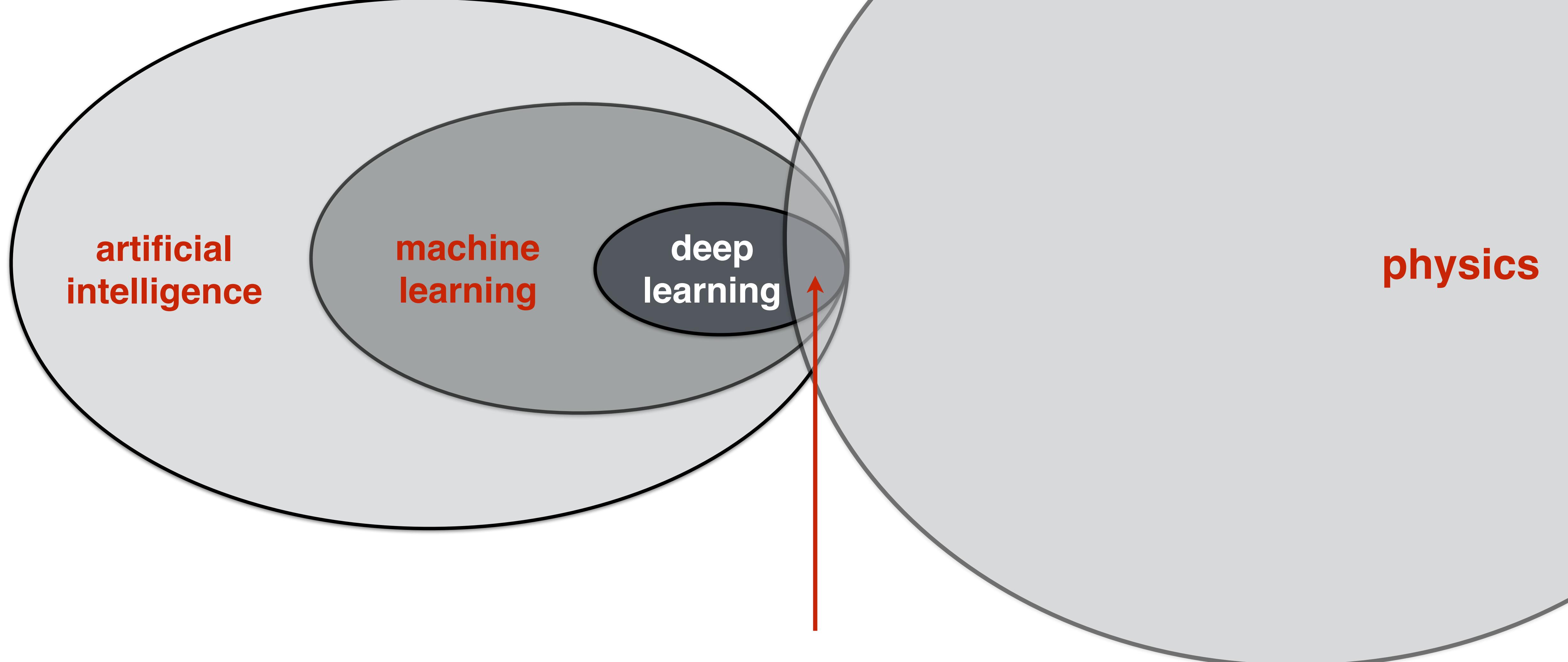
Lei Wang (王磊)

<https://wangleiphy.github.io>

Institute of Physics, Beijing  
Chinese Academy of Sciences



Liu, LW, PRA '18  
Cheng, Chen, LW, Entropy '18  
Han, Wang, Fan, LW, Zhang, PRX '18



**artificial  
intelligence**

**machine  
learning**

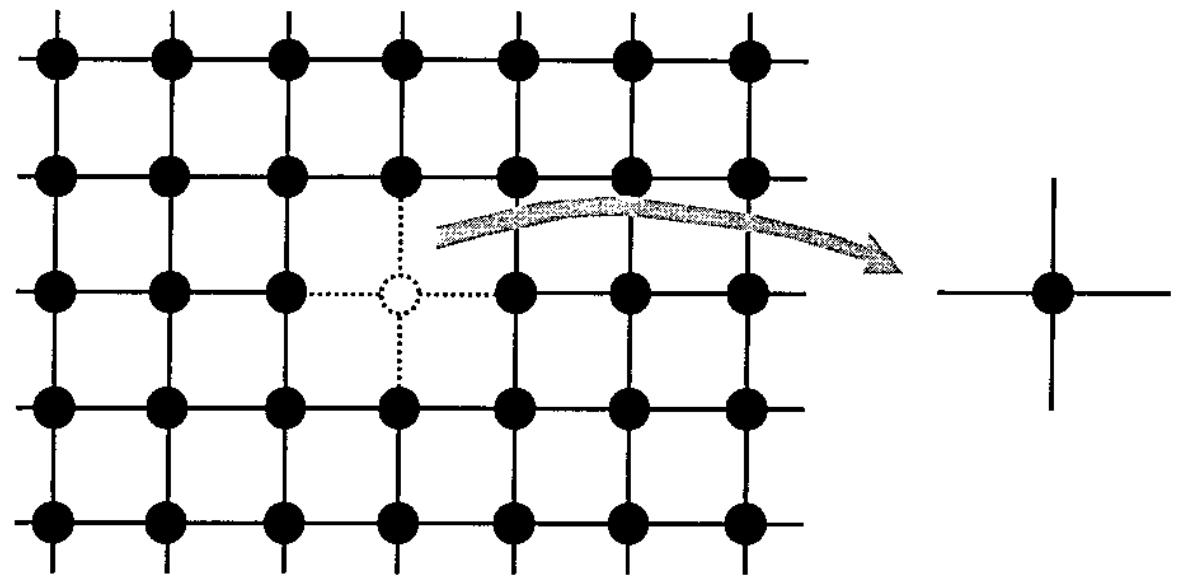
**deep  
learning**

**physics**

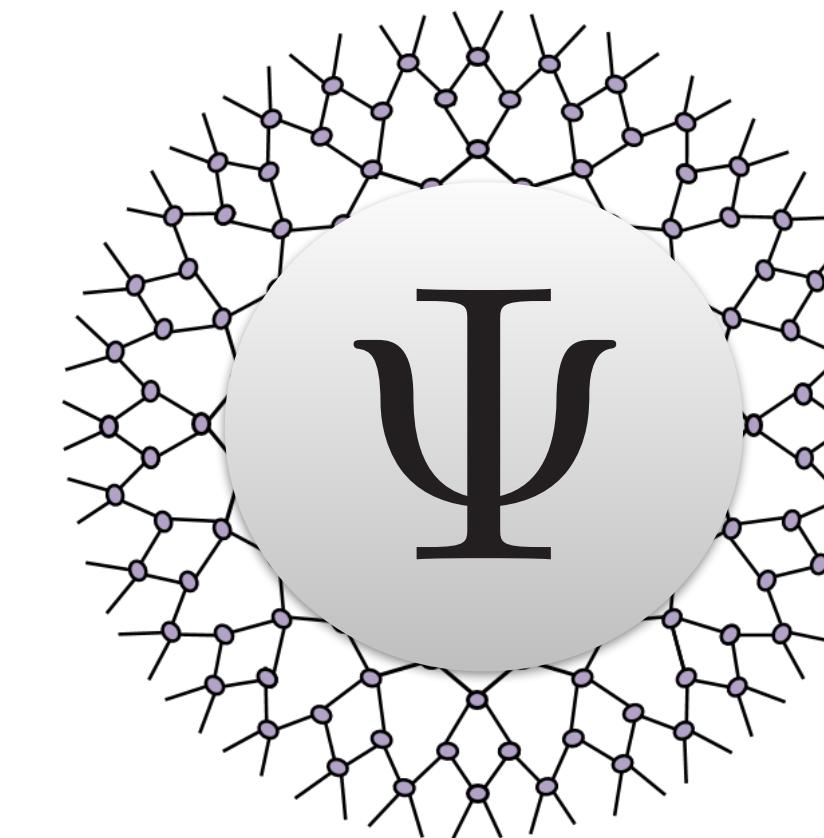
This talk: quantum physics  
for machine learning

# Physicists' gifts to Machine Learning

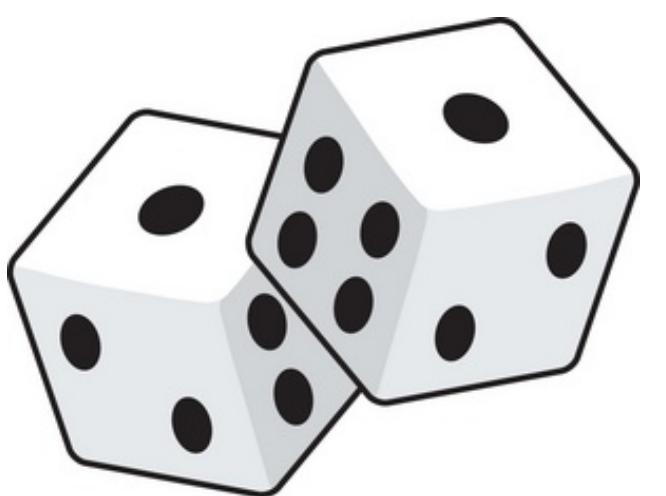
## Mean Field Theory



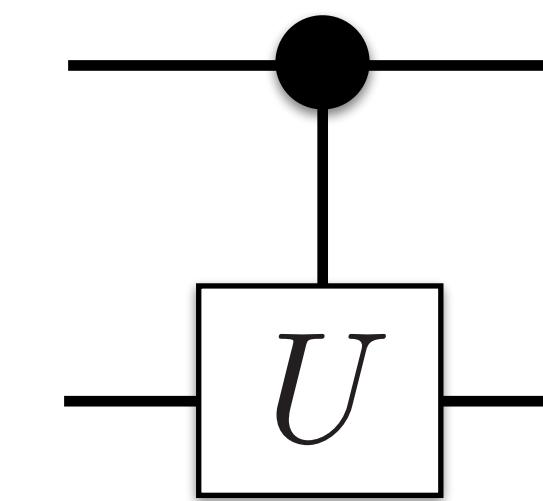
## Tensor Networks



## Monte Carlo Methods



## Quantum Computing



# Learning is more than function fitting

Discriminative



Generative

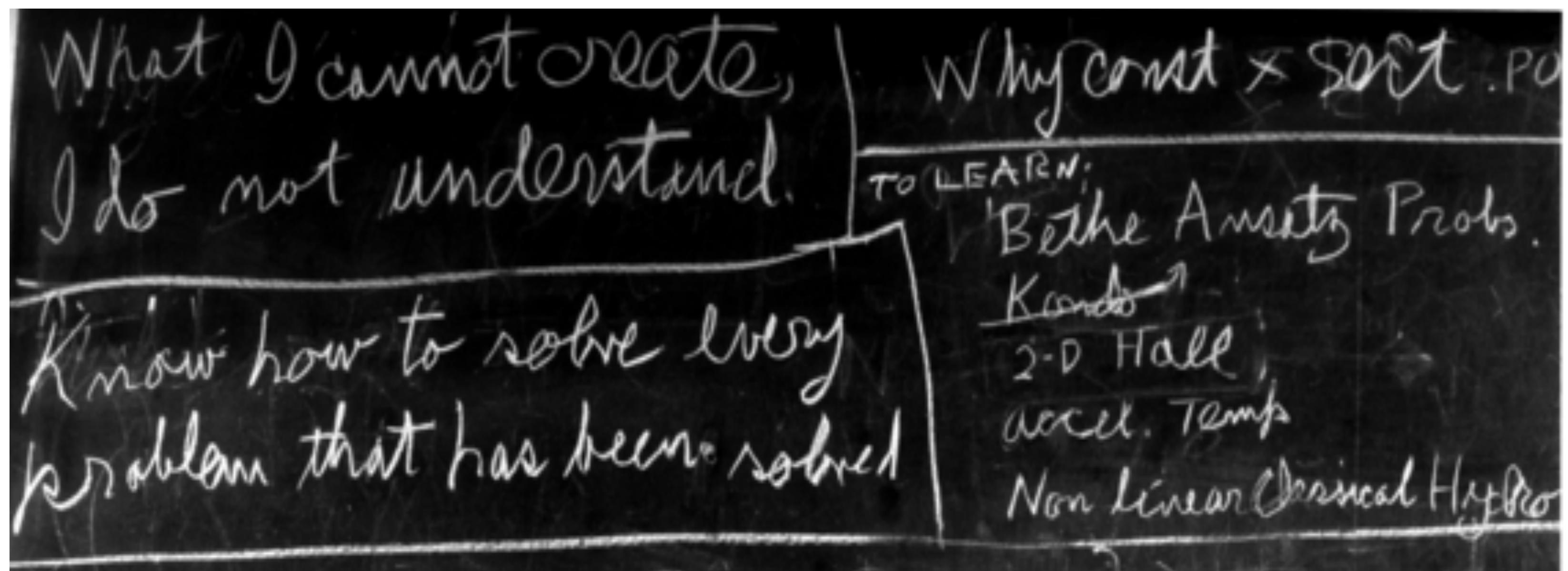
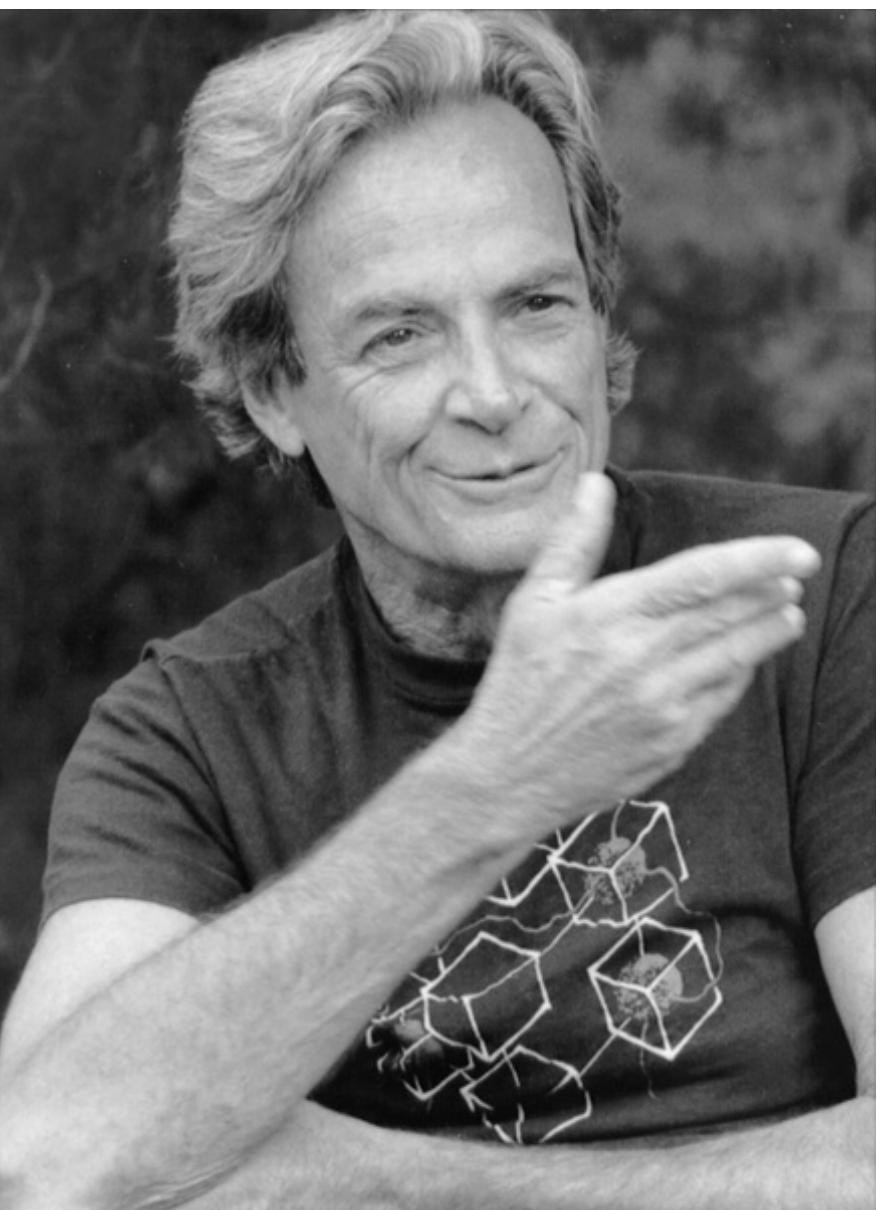


$$y = f(x)$$

or  $p(y | x)$

$$p(x, y)$$

# Learning is more than function fitting



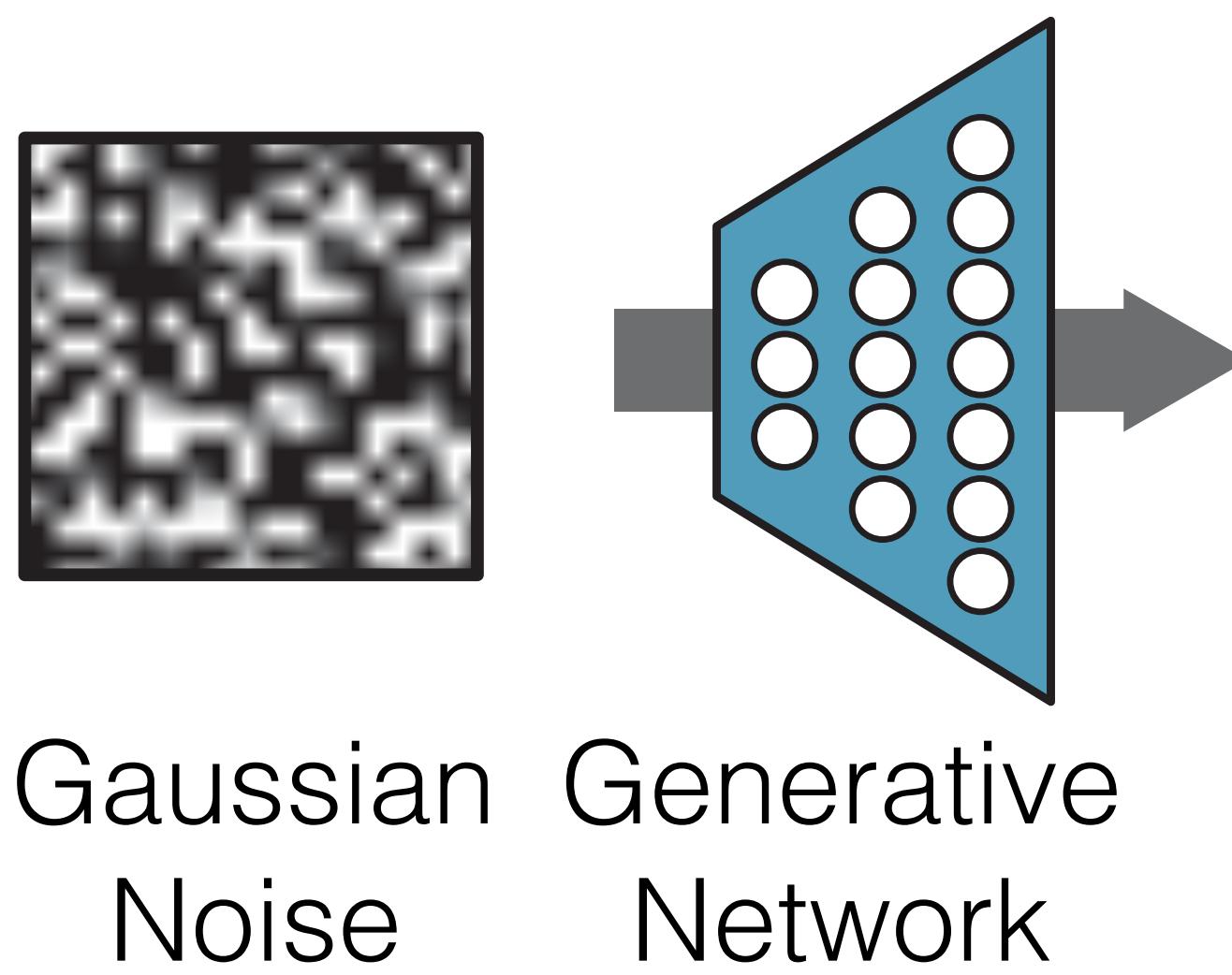
“What I can not create, I do not understand”

# Generated Arts

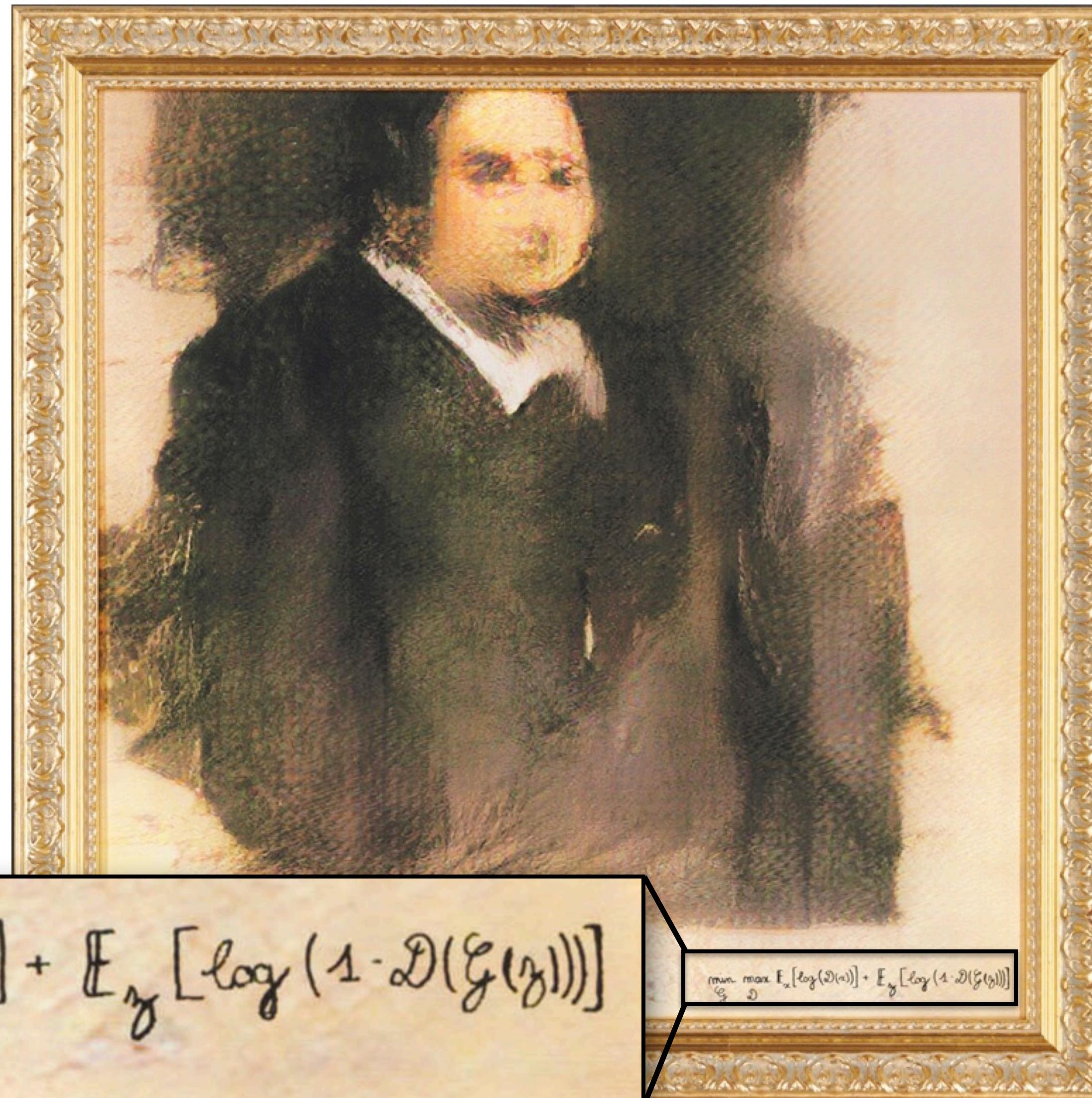


**\$432,500**  
**25 October 2018**  
**Christie's New York**

# Generated Arts



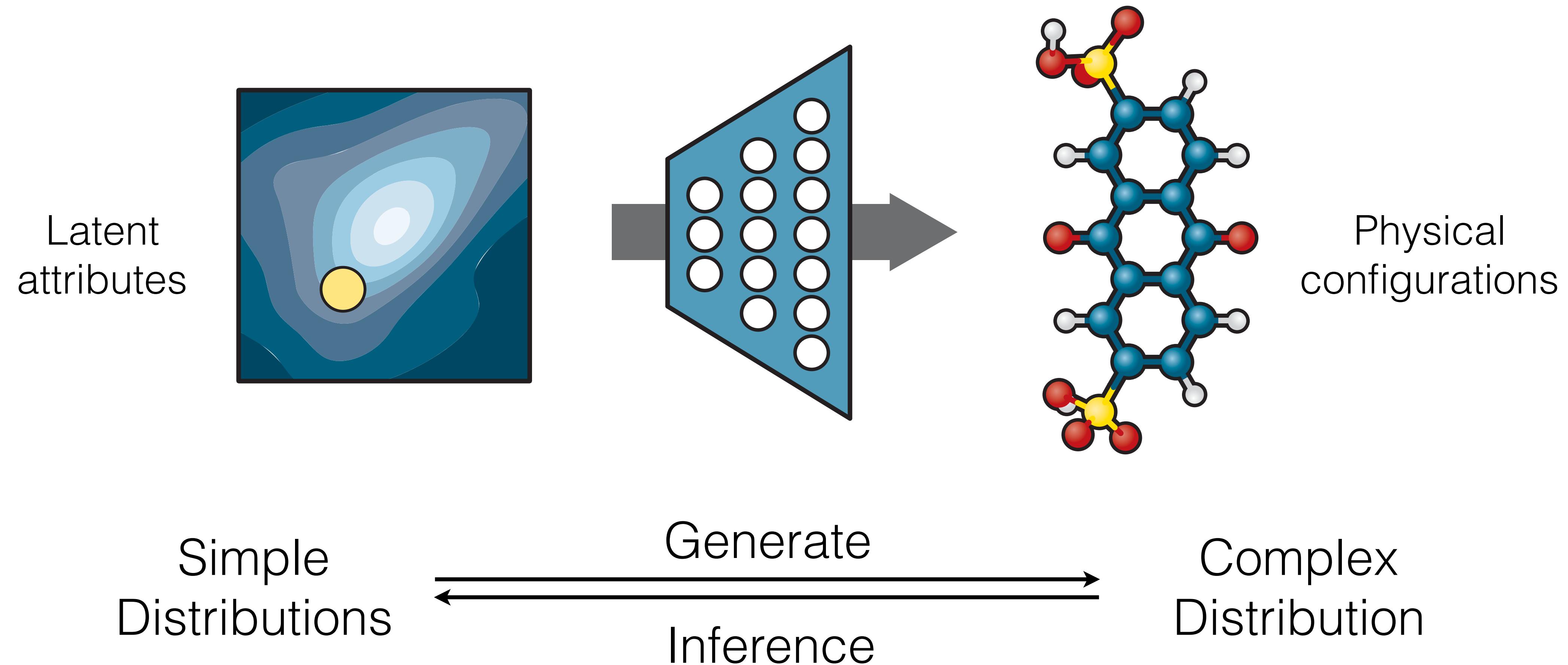
Gaussian Noise      Generative Network



$$\min_{\mathcal{G}} \max_{\mathcal{D}} \mathbb{E}_{\mathbf{x}} [\log(\mathcal{D}(\mathbf{x}))] + \mathbb{E}_{\mathbf{z}} [\log(1 - \mathcal{D}(\mathcal{G}(\mathbf{z})))]$$

\$432,500  
25 October 2018  
Christie's New York

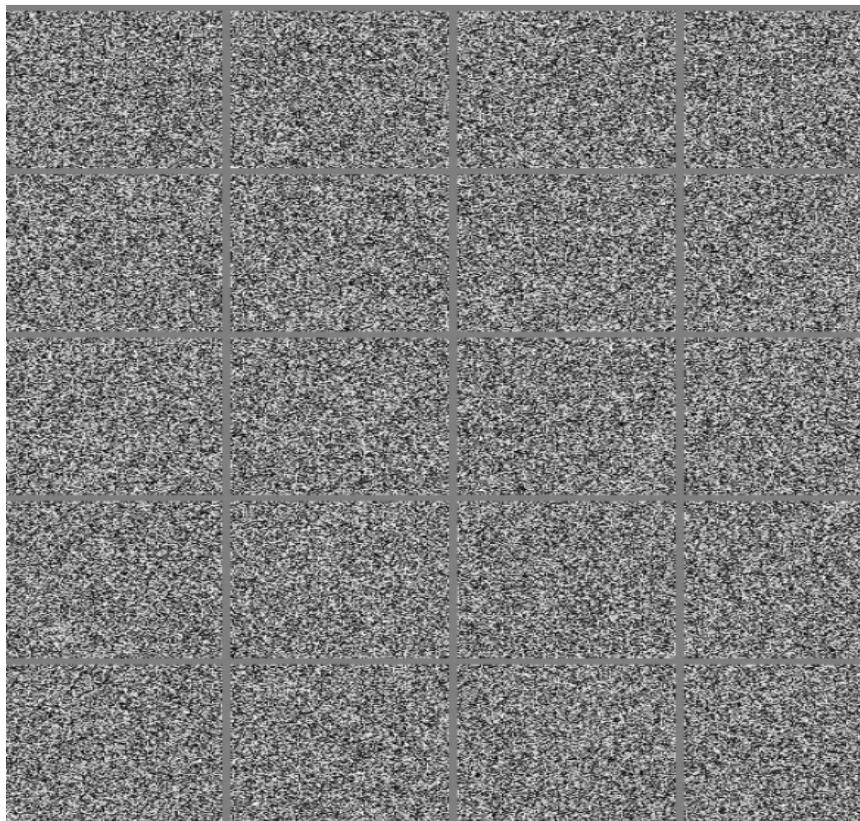
# Generate Molecules



# Probabilistic Generative Modeling

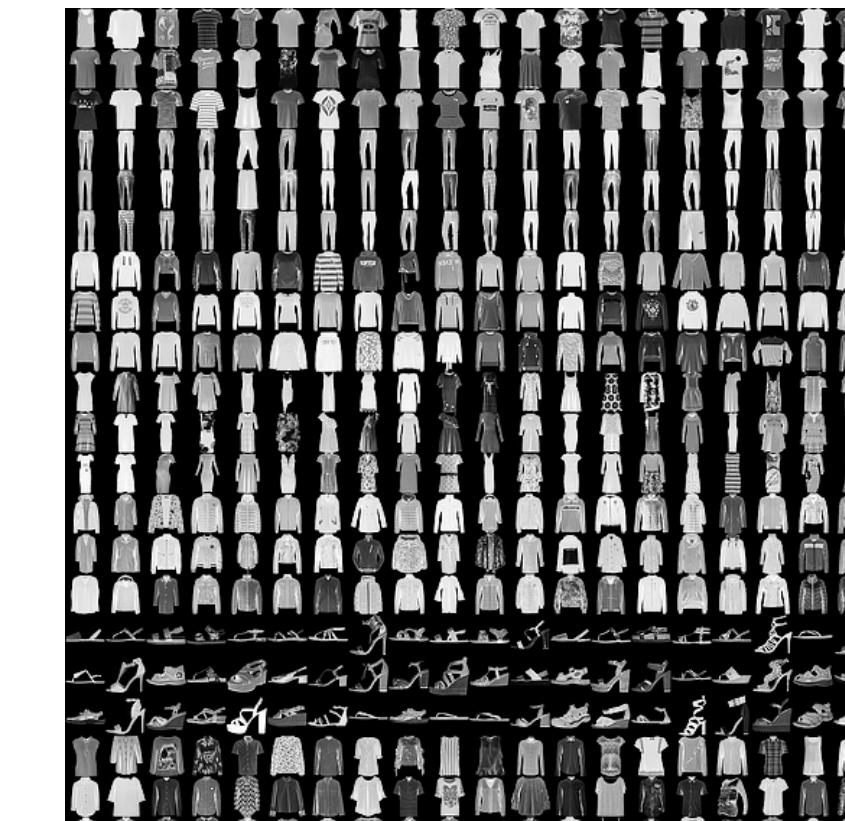
$$p(x)$$

How to express, learn, and sample from a high-dimensional probability distribution ?



“random” images

8	9	0	1	2	3	4	7	8	9	0	1	2	3	4	5	6	7	8	6
4	2	6	4	7	5	5	4	7	8	9	2	9	3	9	3	8	2	0	5
0	1	0	4	2	6	5	3	5	3	8	0	0	3	4	1	5	3	0	8
3	0	6	2	7	1	1	8	1	7	1	3	8	9	7	6	7	4	1	6
7	5	1	7	1	9	8	0	6	9	4	9	9	3	7	1	9	2	2	5
3	7	8	2	3	4	5	6	7	8	9	0	1	2	3	4	5	6	7	0
1	2	3	4	5	6	7	8	9	8	1	0	5	5	1	9	0	4	1	9
3	8	4	7	7	8	5	0	6	5	5	3	3	3	9	8	1	4	0	6
1	0	0	6	2	1	1	3	2	8	8	7	8	4	6	0	2	0	3	6
8	7	1	5	9	9	3	2	4	9	4	4	5	3	2	8	5	9	4	1
6	5	0	1	2	3	4	5	6	7	8	9	0	1	2	3	4	5	6	7
8	9	0	1	2	3	4	5	6	7	8	9	6	4	2	6	4	7	5	5
4	7	8	9	2	9	3	9	3	8	2	0	9	8	0	5	6	0	1	0
4	2	6	5	5	5	4	3	4	1	5	3	0	8	3	0	6	2	7	1
1	8	1	7	1	3	8	5	4	2	0	9	7	6	7	4	1	6	8	4
7	5	1	2	6	7	1	9	8	0	6	9	4	9	9	6	2	3	7	1
9	2	2	5	3	7	8	0	1	2	3	4	5	6	7	8	0	1	2	3
4	5	6	7	8	0	1	2	3	4	5	6	7	8	9	2	1	2	1	3
9	9	8	5	3	7	0	7	7	5	7	9	9	4	7	0	3	4	1	4
4	7	5	8	1	4	8	4	1	8	6	4	6	3	5	7	2	5	9	



“natural” images

# Probabilistic modeling

How to  
high-d

from a  
solution ?

Page 159

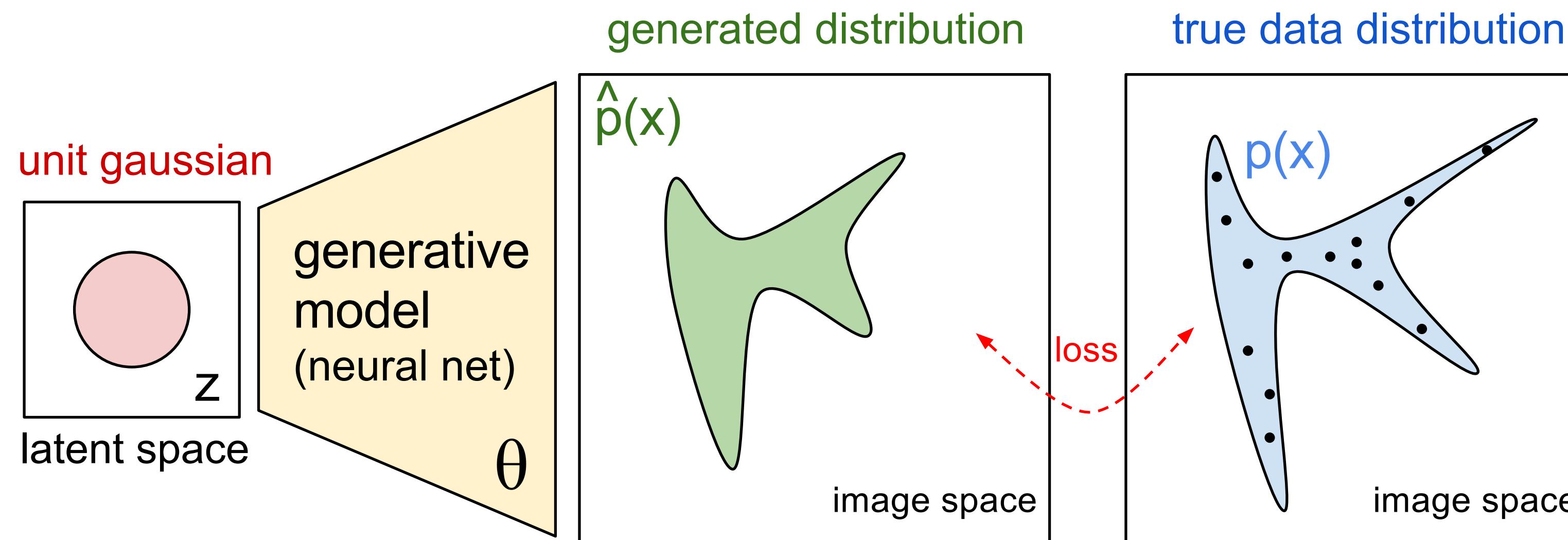
*“... the images encountered in  
AI applications occupy a  
negligible proportion of  
the volume of image space.”*

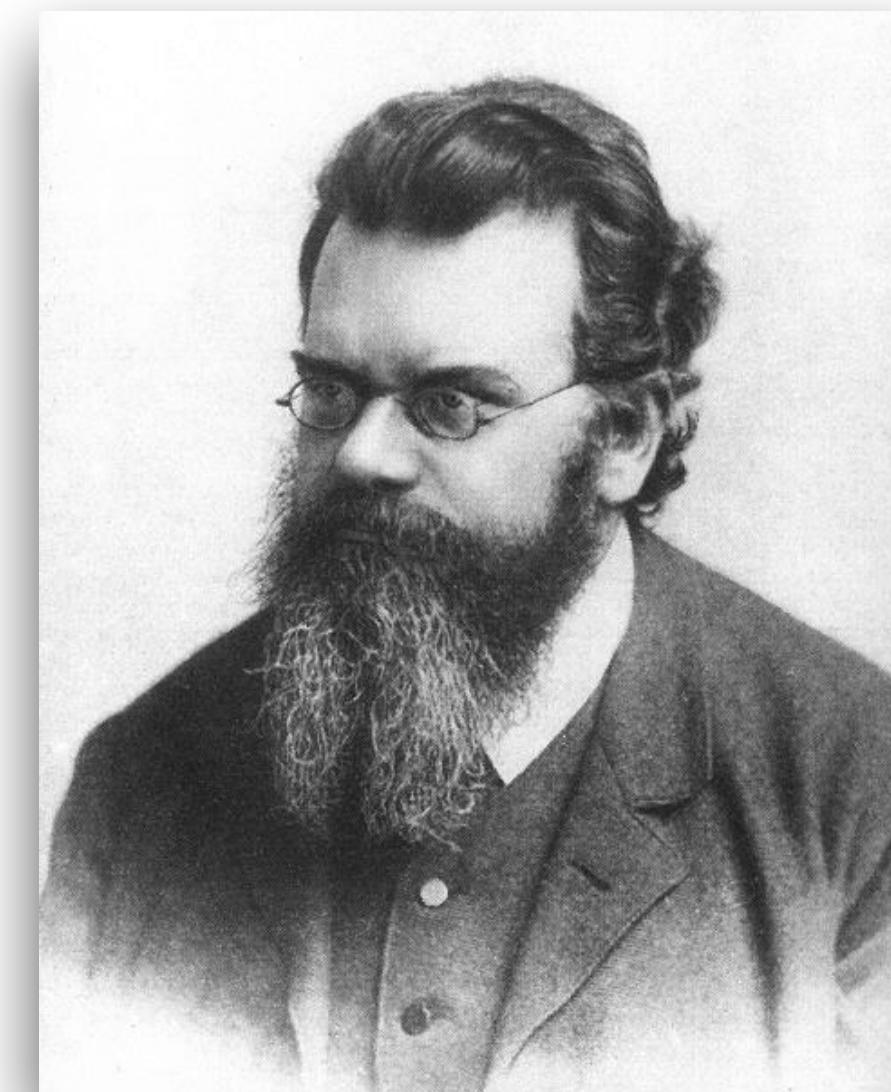
“random”

# Probabilistic Generative Modeling

$$p(x)$$

How to express, learn, and sample from a high-dimensional probability distribution ?





# *Boltzmann Machines*

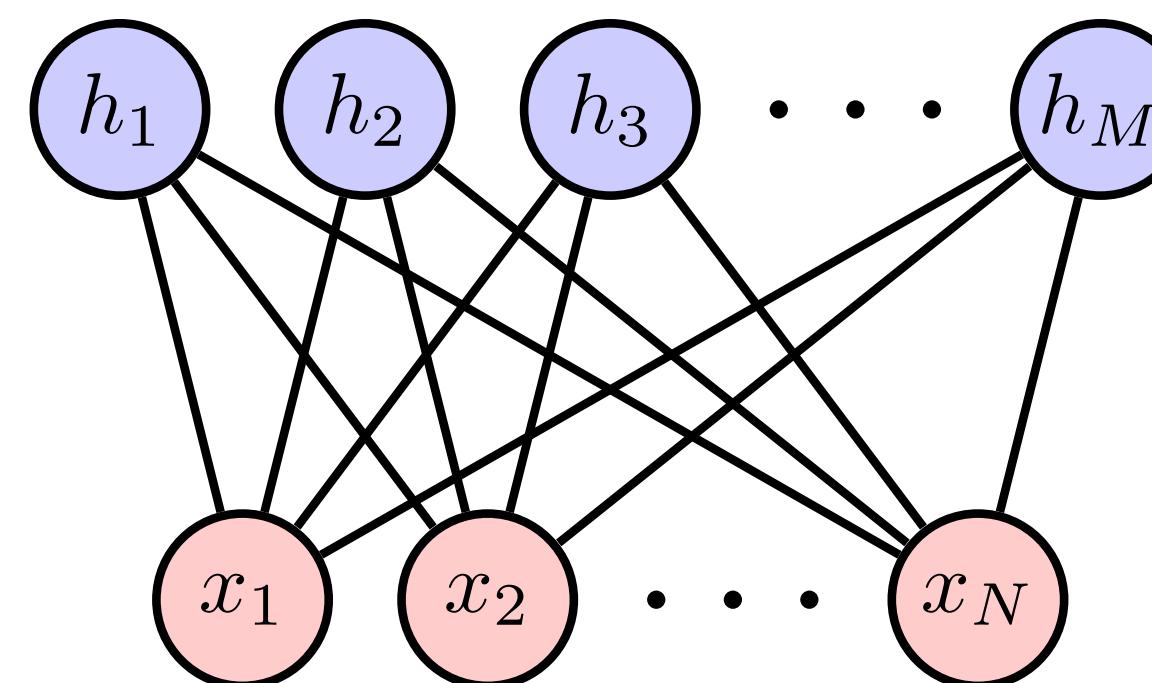
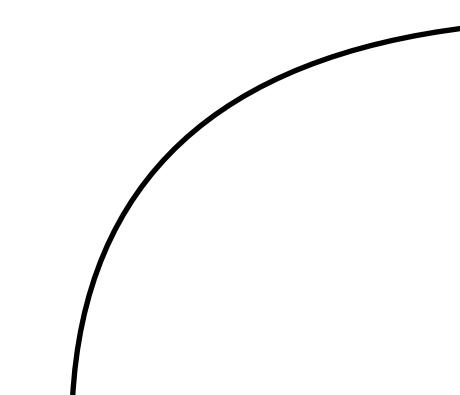
$$p(x) = \frac{e^{-E(x)}}{Z}$$

statistical physics

# Generative Modeling using Boltzmann Machines

Negative log-likelihood loss  $\mathcal{L} = -\frac{1}{|\mathcal{D}|} \sum_{x \in \mathcal{D}} \ln p(x)$

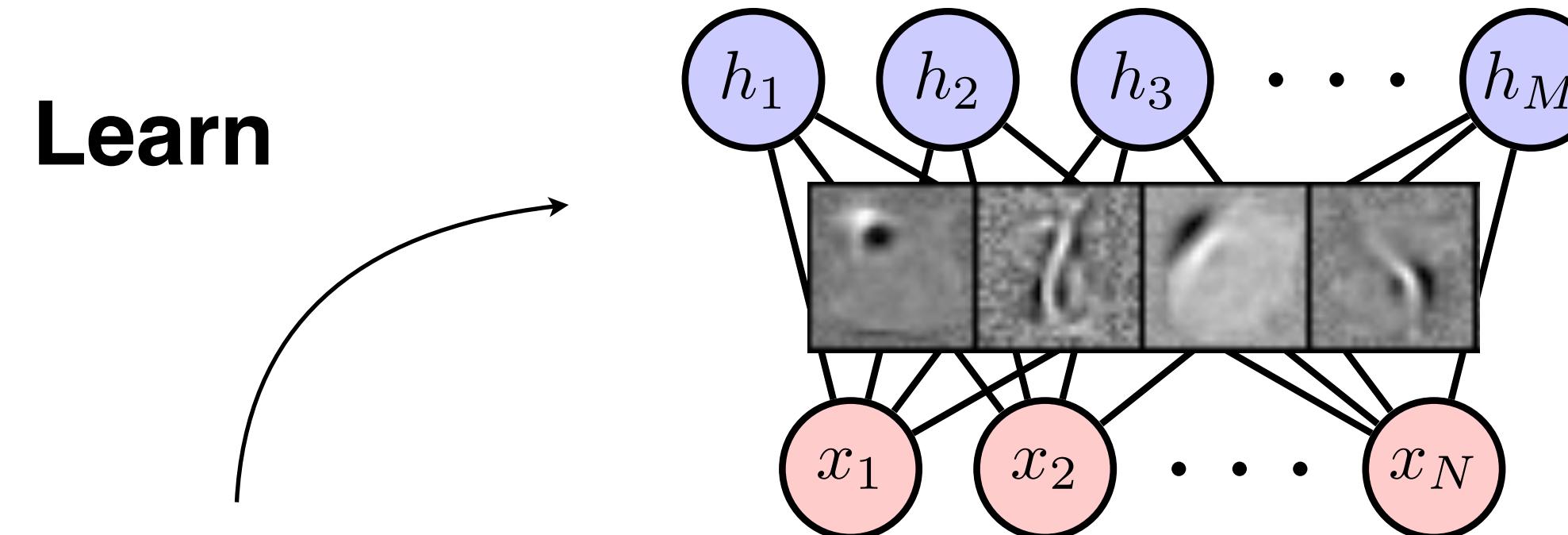
**Learn**



6	2	7	4	2	1	9
1	2	5	3	0	7	5
8	1	8	4	2	6	6
0	7	9	8	6	3	2
7	5	0	5	7	9	5
1	8	7	0	6	5	0
7	5	4	8	4	4	7

# Generative Modeling using Boltzmann Machines

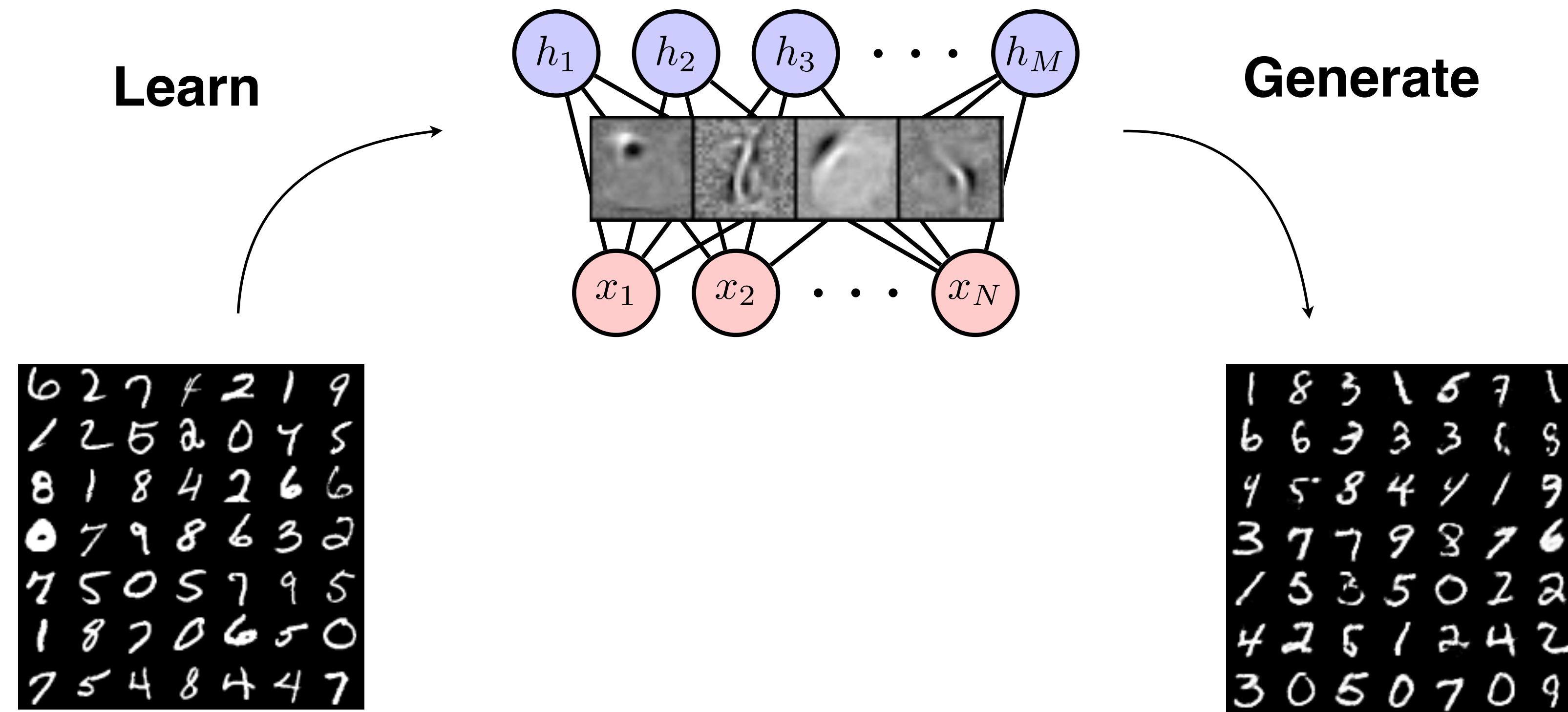
Negative log-likelihood loss  $\mathcal{L} = -\frac{1}{|\mathcal{D}|} \sum_{x \in \mathcal{D}} \ln p(x)$



6	2	7	4	2	1	9
1	2	5	3	0	7	5
8	1	8	4	2	6	6
0	7	9	8	6	3	2
7	5	0	5	7	9	5
1	8	7	0	6	5	0
7	5	4	8	4	4	7

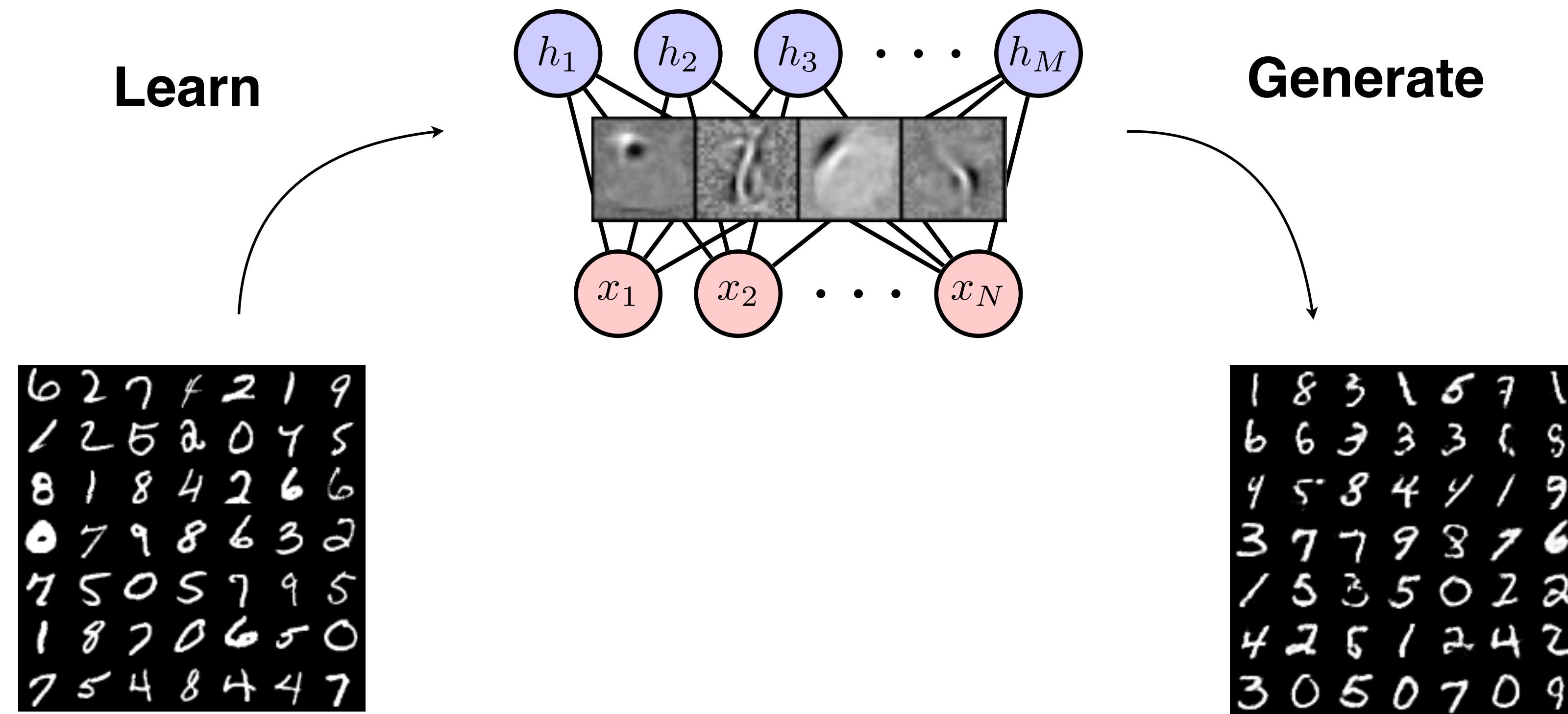
# Generative Modeling using Boltzmann Machines

Negative log-likelihood loss  $\mathcal{L} = -\frac{1}{|\mathcal{D}|} \sum_{x \in \mathcal{D}} \ln p(x)$



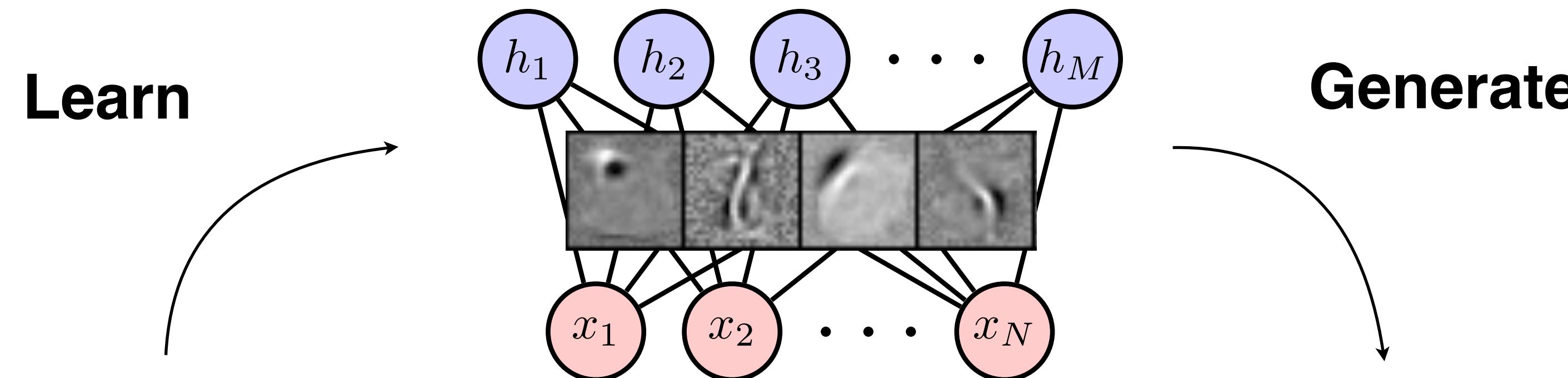
# Generative Modeling using Boltzmann Machines

Negative log-likelihood loss  $\mathcal{L} = -\frac{1}{|\mathcal{D}|} \sum_{x \in \mathcal{D}} \ln p(x) = \langle E(x) \rangle_{x \sim \mathcal{D}} + \ln Z$



# Generative Modeling using Boltzmann Machines

Negative log-likelihood loss  $\mathcal{L} = -\frac{1}{|\mathcal{D}|} \sum_{x \in \mathcal{D}} \ln p(x) = \langle E(x) \rangle_{x \sim \mathcal{D}} + \ln Z$



Learn

6	2	7	4	2	1	9
1	2	5	3	0	7	5
8	1	8	4	2	6	6
0	7	9	8	6	3	2
7	5	0	5	7	9	5
1	8	7	0	6	5	0
7	5	4	8	4	4	7

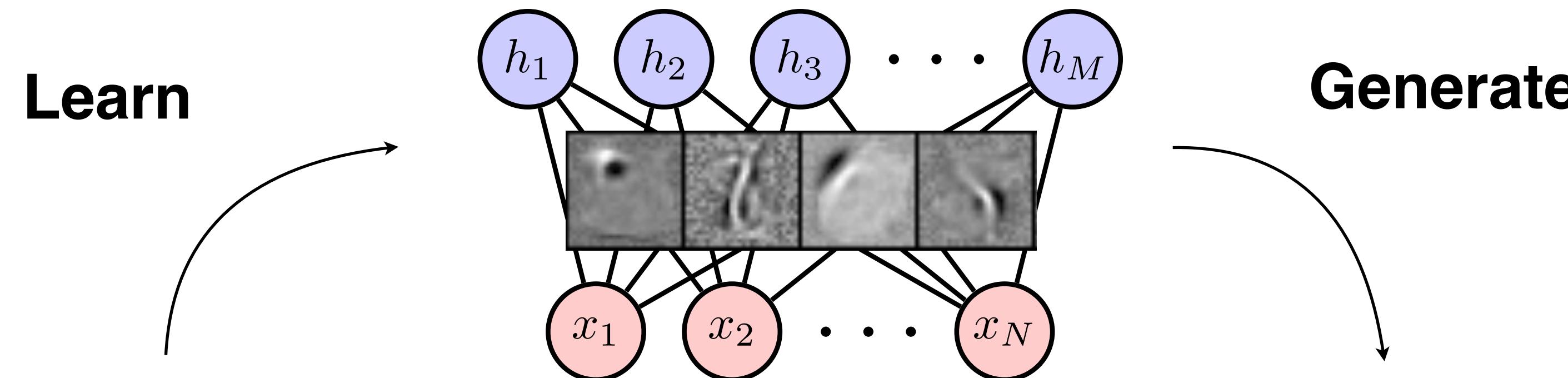
$$\nabla \mathcal{L} = \langle \nabla E \rangle_{x \sim \mathcal{D}} - \langle \nabla E \rangle_{x \sim p(x)}$$

Generate

1	8	3	1	6	7	1
6	6	3	3	3	6	8
4	5	8	4	4	1	9
3	7	7	9	8	7	6
1	5	3	5	0	2	2
4	2	5	1	2	4	2
3	0	5	0	7	0	9

# Generative Modeling using Boltzmann Machines

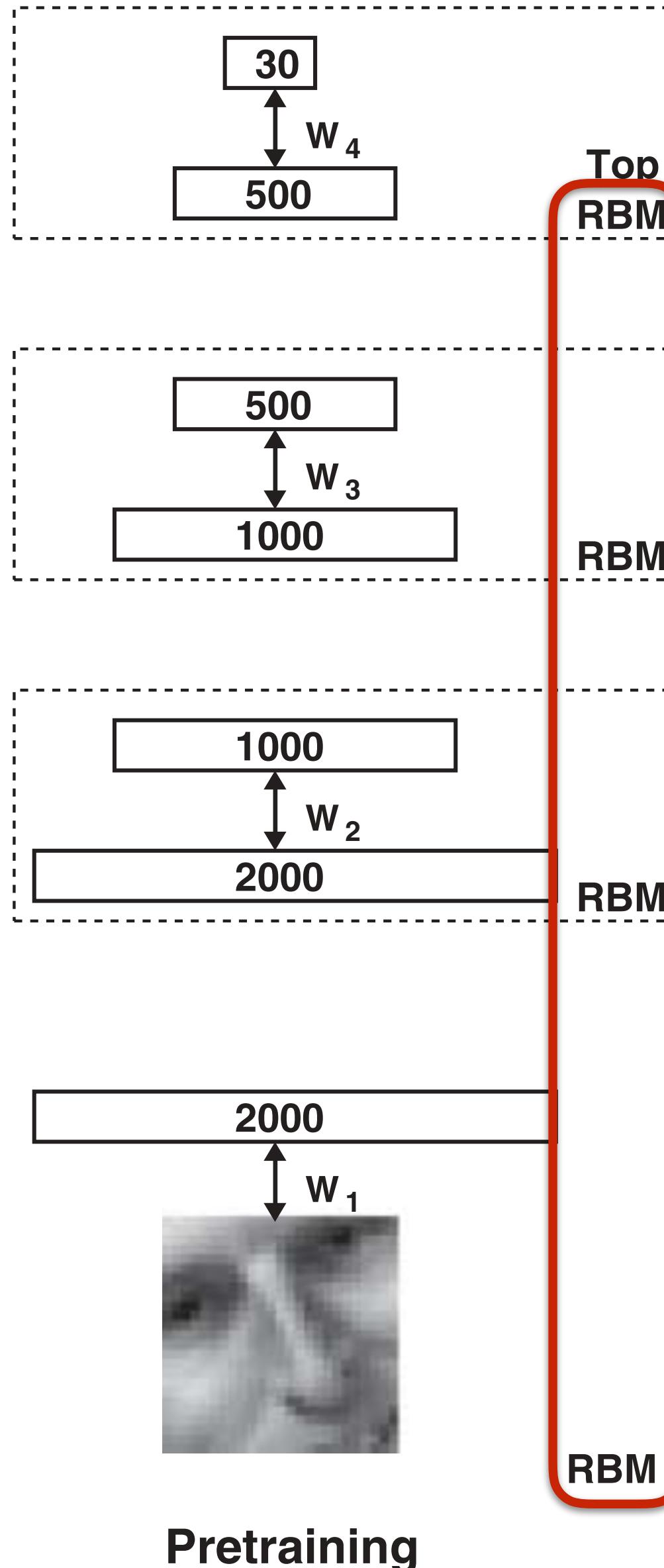
Negative log-likelihood loss  $\mathcal{L} = -\frac{1}{|\mathcal{D}|} \sum_{x \in \mathcal{D}} \ln p(x) = \langle E(x) \rangle_{x \sim \mathcal{D}} + \ln Z$



6	2	7	4	2	1	9
1	2	5	3	0	7	5
8	1	8	4	2	6	6
0	7	9	8	6	3	2
7	5	0	5	7	9	5
1	8	7	0	6	5	0
7	5	4	8	4	4	7

$$\nabla \mathcal{L} = \langle \nabla E \rangle_{x \sim \mathcal{D}} - \langle \nabla E \rangle_{x \sim p(x)}$$

1	8	3	1	6	7	1
6	6	3	3	3	6	8
4	5	8	4	4	1	9
3	7	7	9	8	7	6
1	5	3	5	0	2	2
4	2	5	1	2	4	2
3	0	5	0	7	0	9



# Reducing the Dimensionality of Data with Neural Networks

G. E. Hinton\* and R. R. Salakhutdinov

High-dimensional data can be converted to low-dimensional codes by training a multilayer neural network with a small central layer to reconstruct high-dimensional input vectors. Gradient descent can be used for fine-tuning the weights in such “autoencoder” networks, but this works well only if the initial weights are close to a good solution. We describe an effective way of initializing the weights that allows deep autoencoder networks to learn low-dimensional codes that work much better than principal components analysis as a tool to reduce the dimensionality of data.

Dimensionality reduction facilitates the classification, visualization, communication, and storage of high-dimensional data. A simple and widely used method is principal components analysis (PCA), which

finds the directions of greatest variance in the data set and represents each data point by its coordinates along each of these directions. We describe a nonlinear generalization of PCA that uses an adaptive, multilayer “encoder” network

2006 VOL 313 SCIENCE [www.sciencemag.org](http://www.sciencemag.org)

## Renaissance of deep learning

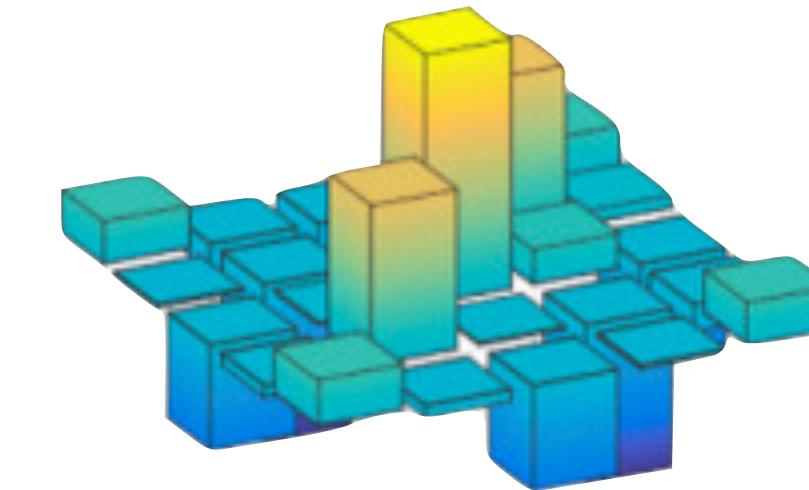


# Feedback to Physics

$\Psi$

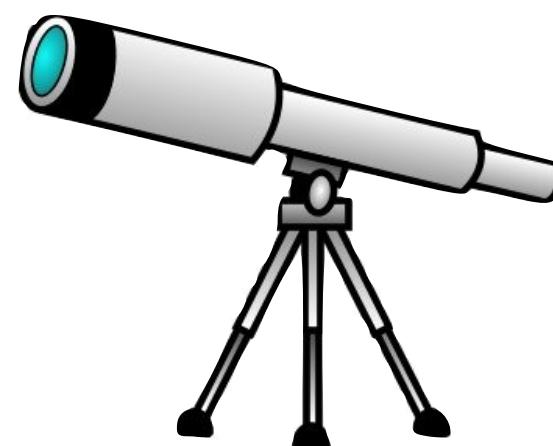
**Wavefunctions ansatz**

Carleo, Troyer...



**Quantum tomography**

Torlai, Melko, Carrasquilla...



**Renormalization group**

Beny, Metha, Schwab, ...

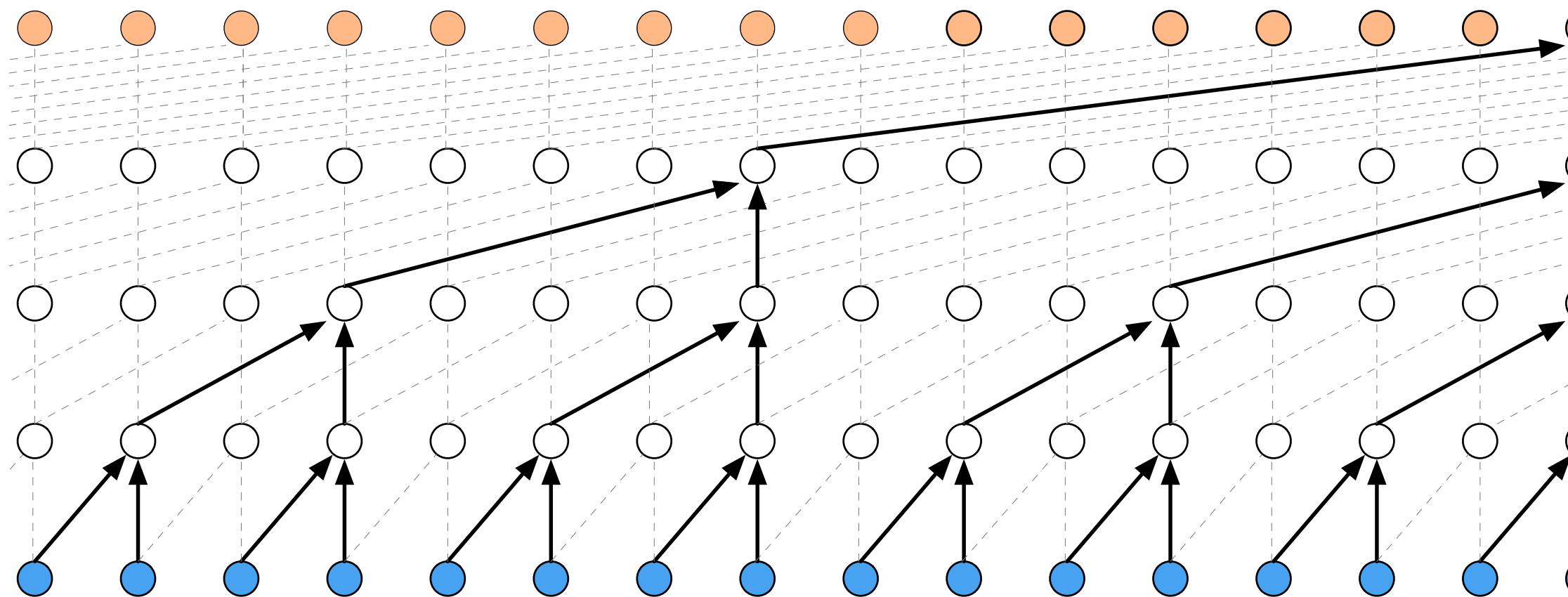


**Monte Carlo update**

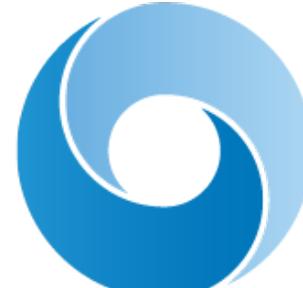
Huang, Liu, ...

# State-of-the-Art: Autoregressive Models

$$p(\mathbf{x}) = \prod_i p(x_i | \mathbf{x}_{<i})$$



Speech data



WaveNet 1609.03499, 1711.10433

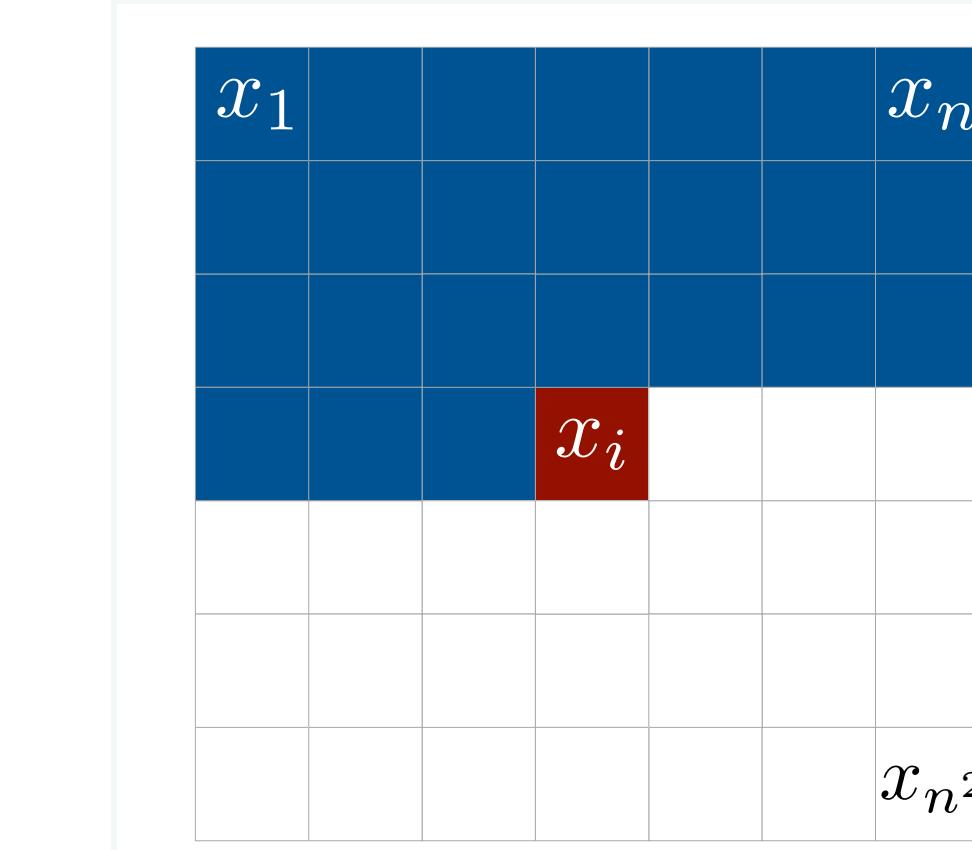
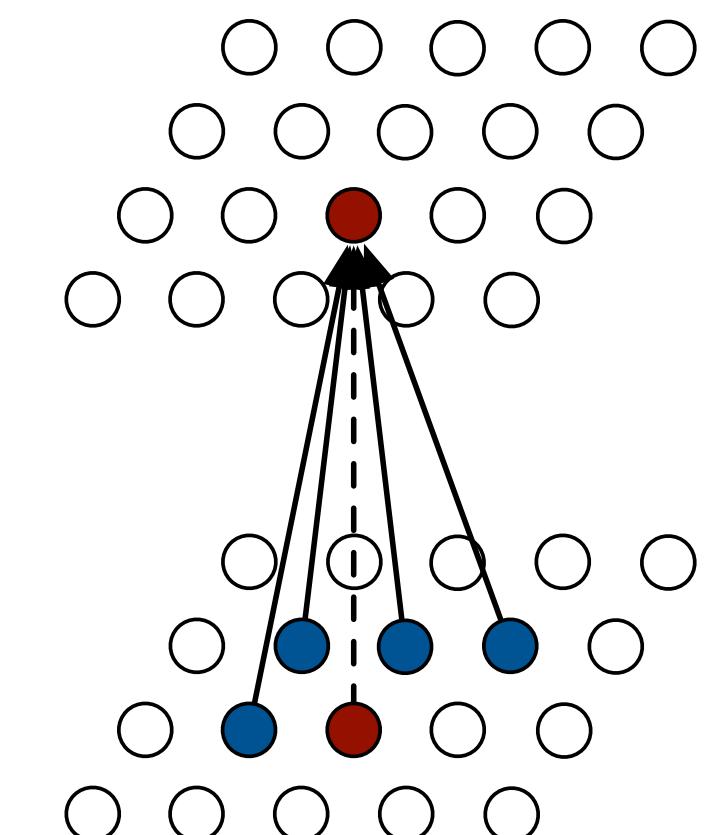


Image data

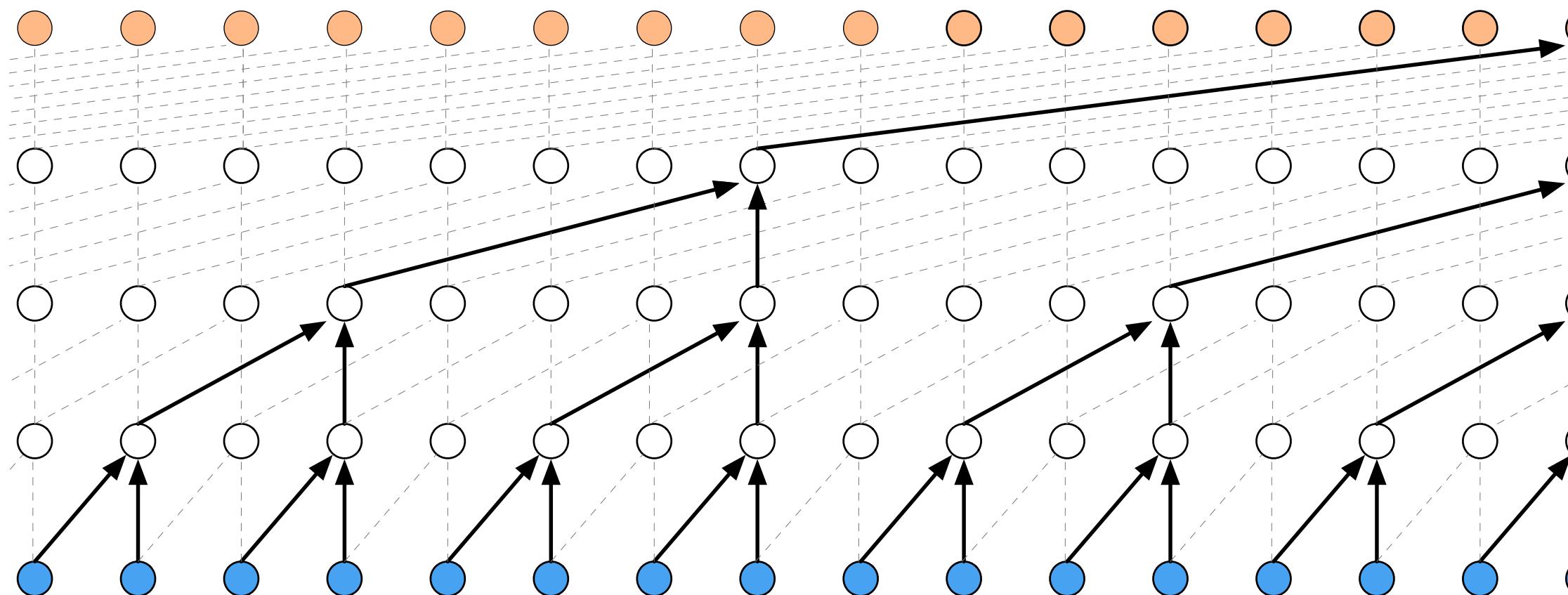


PixelCNN 1601.06759, 1606.05328



# State-of-the-Art: Autoregressive Models

$$\begin{aligned} p(\mathbf{x}) &= \prod p(x_i | \mathbf{x}_{<i}) \\ &= p(x_1)p(x_2 | x_1)p(x_3 | x_1, x_2)\cdots \end{aligned}$$



Speech data



WaveNet 1609.03499, 1711.10433

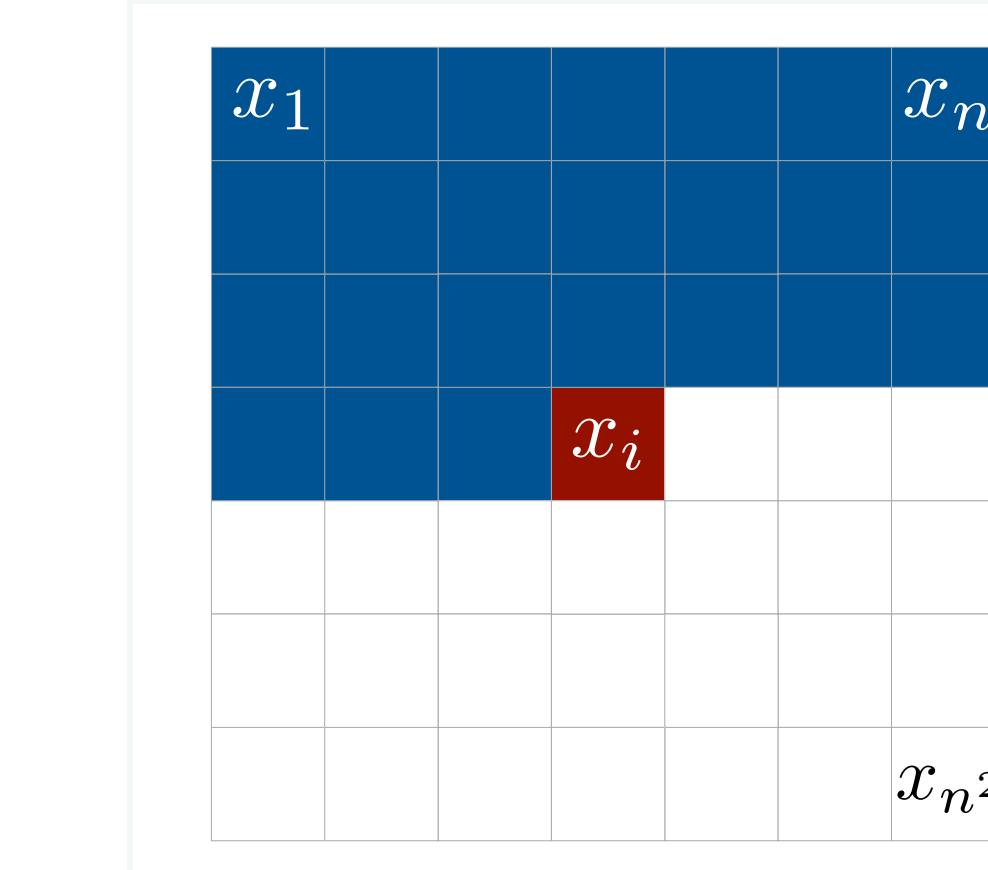
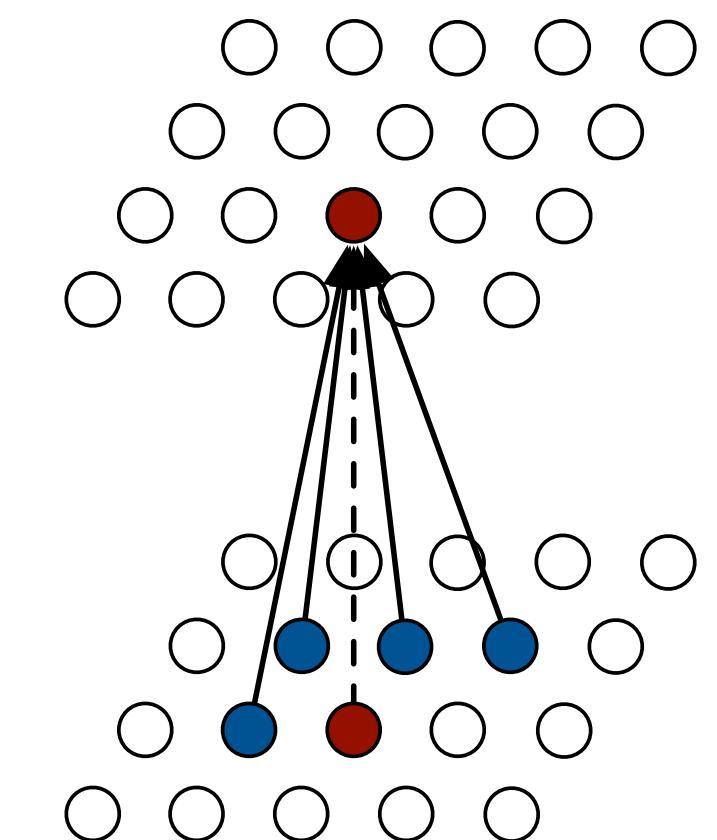


Image data



PixelCNN 1601.06759, 1606.05328



# WaveNet in the Real World



2018 Google I/O

<https://deepmind.com/blog/wavenet-generative-model-raw-audio/>

<https://deepmind.com/blog/high-fidelity-speech-synthesis-wavenet/>

<https://deepmind.com/blog/wavenet-launches-google-assistant/>



# WaveNet in the Real World



2018 Google I/O

<https://deepmind.com/blog/wavenet-generative-model-raw-audio/>

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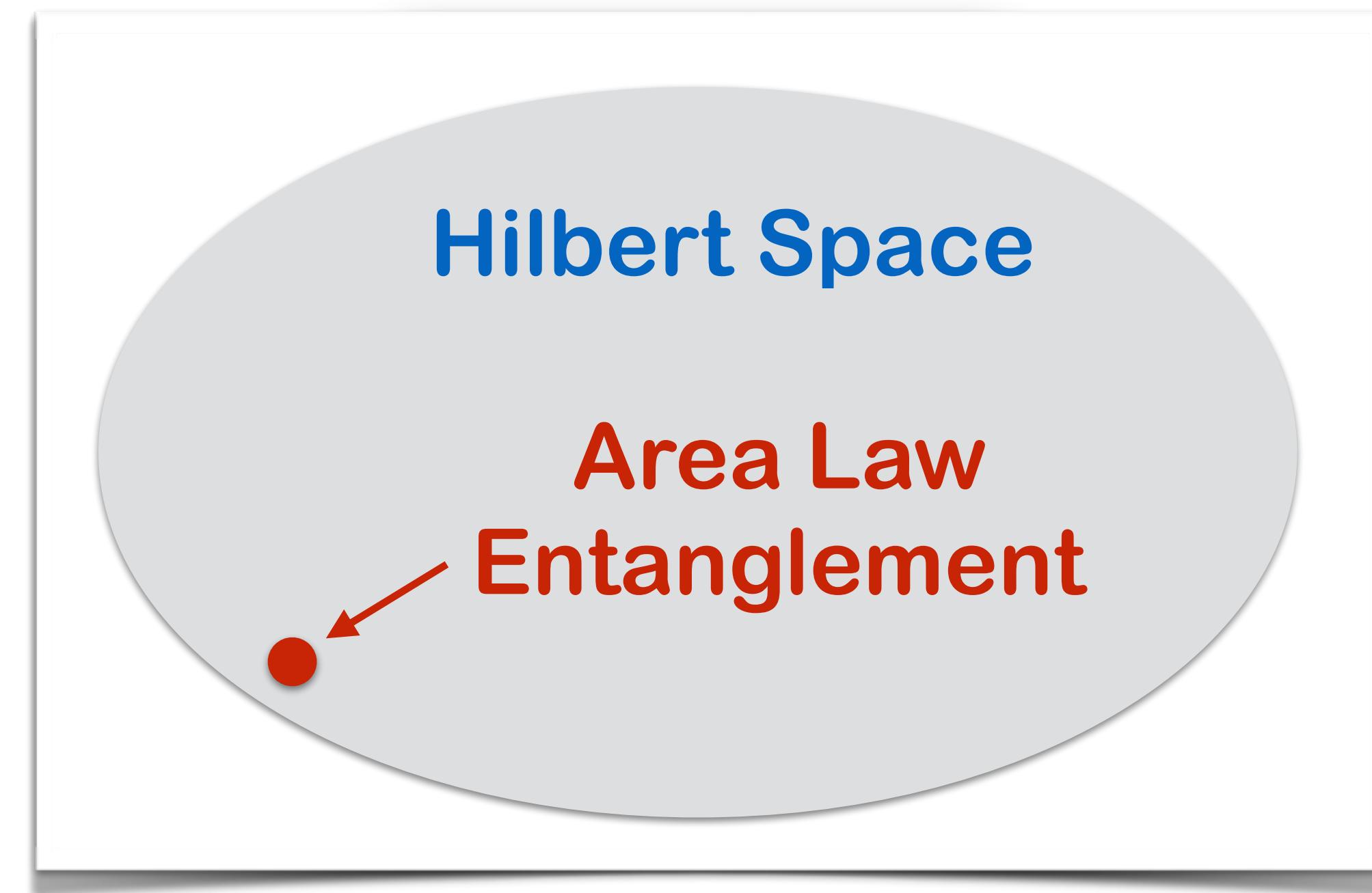




# *Born Machines*

$$p(x) = \frac{|\Psi(x)|^2}{Z}$$

quantum physics

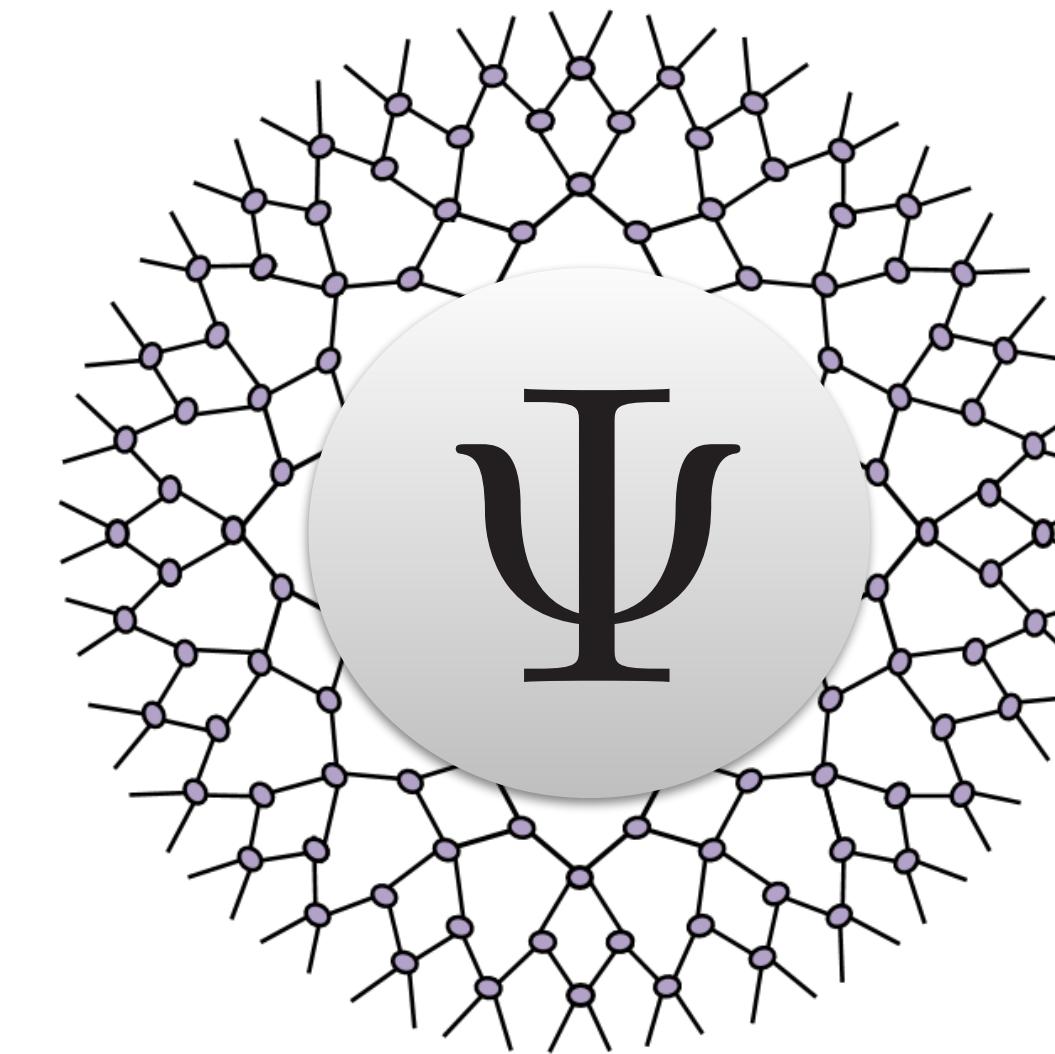


*Born Machines*

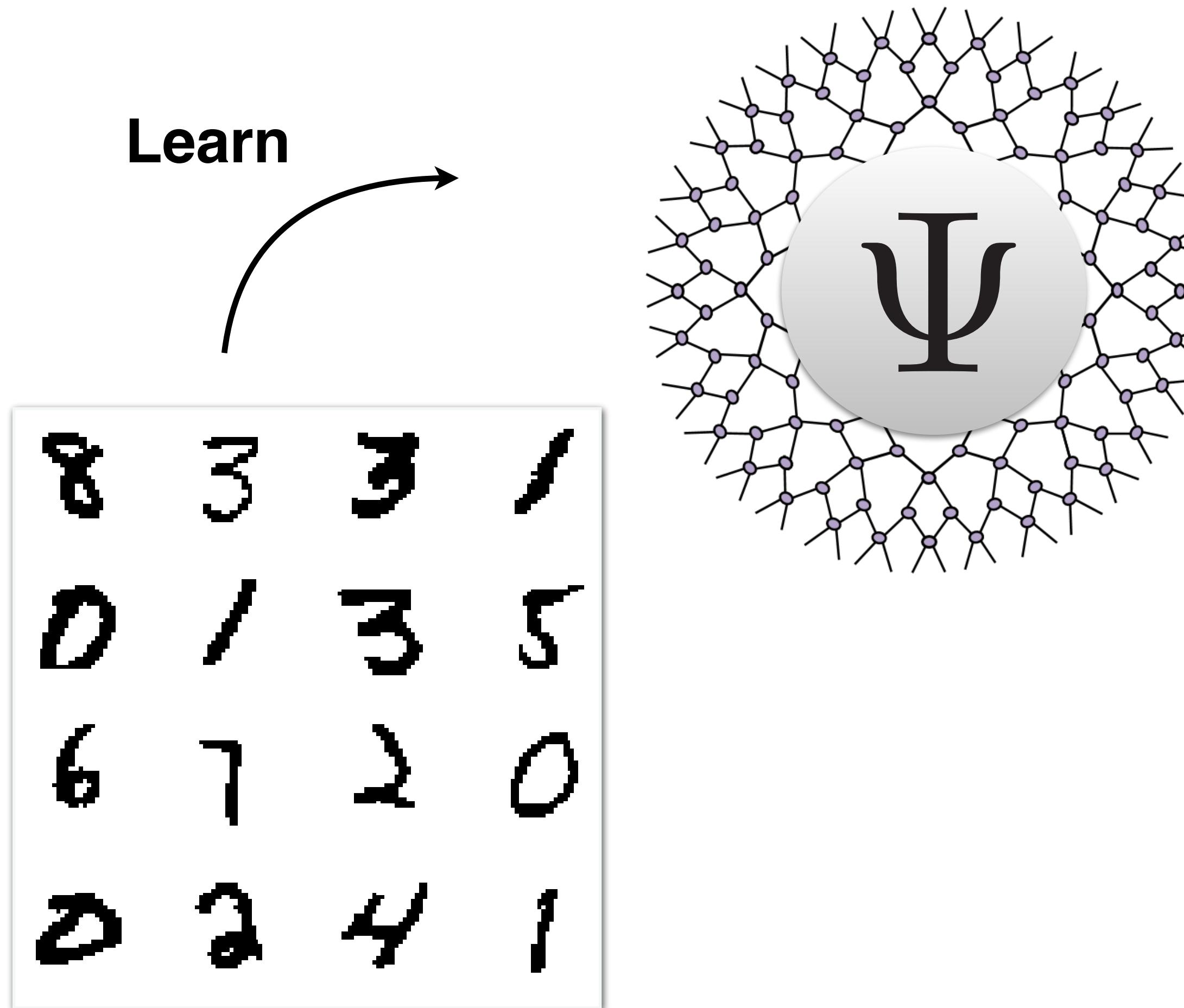
$$p(x) = \frac{|\Psi(x)|^2}{Z}$$

quantum physics

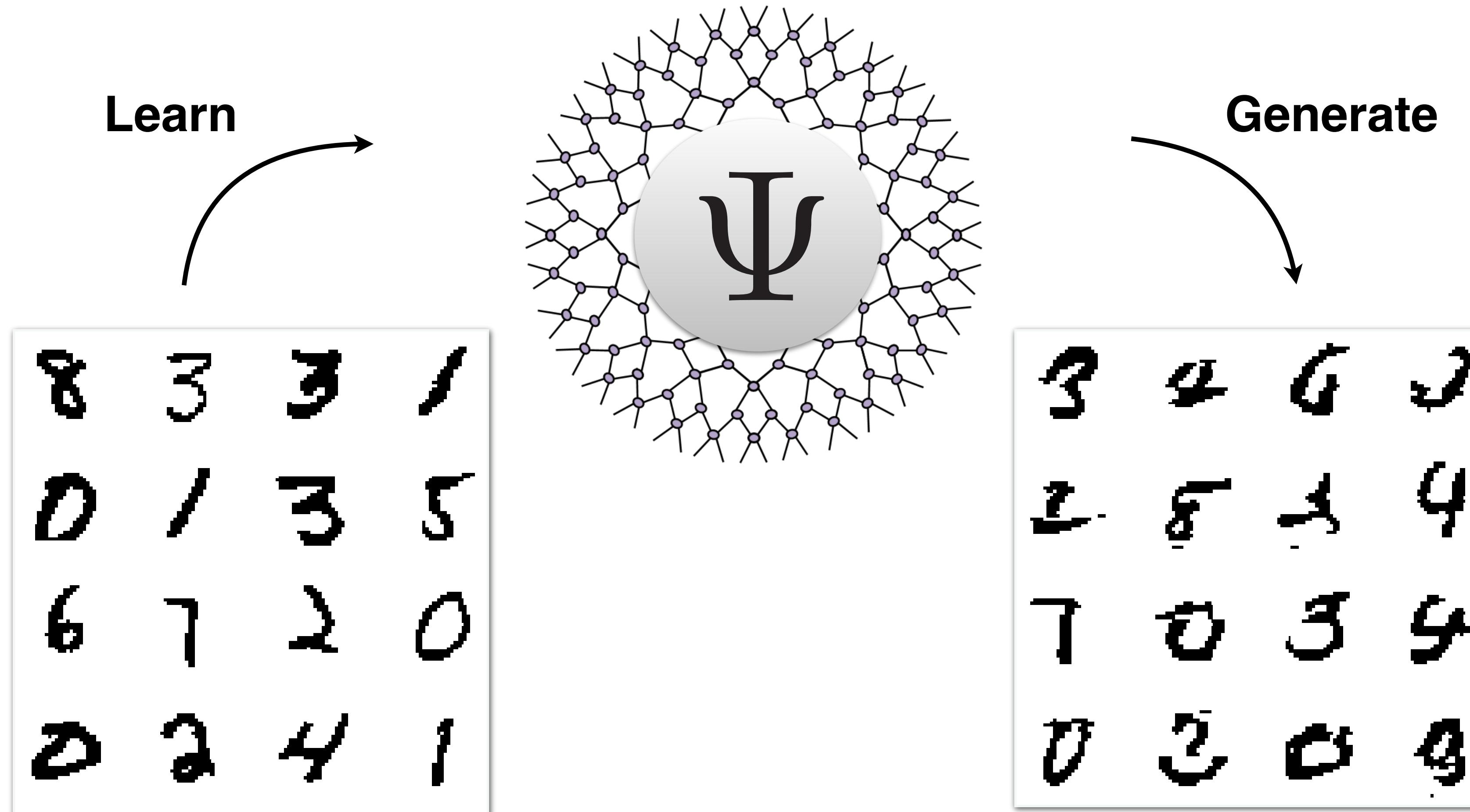
# Quantum inspired generative modeling



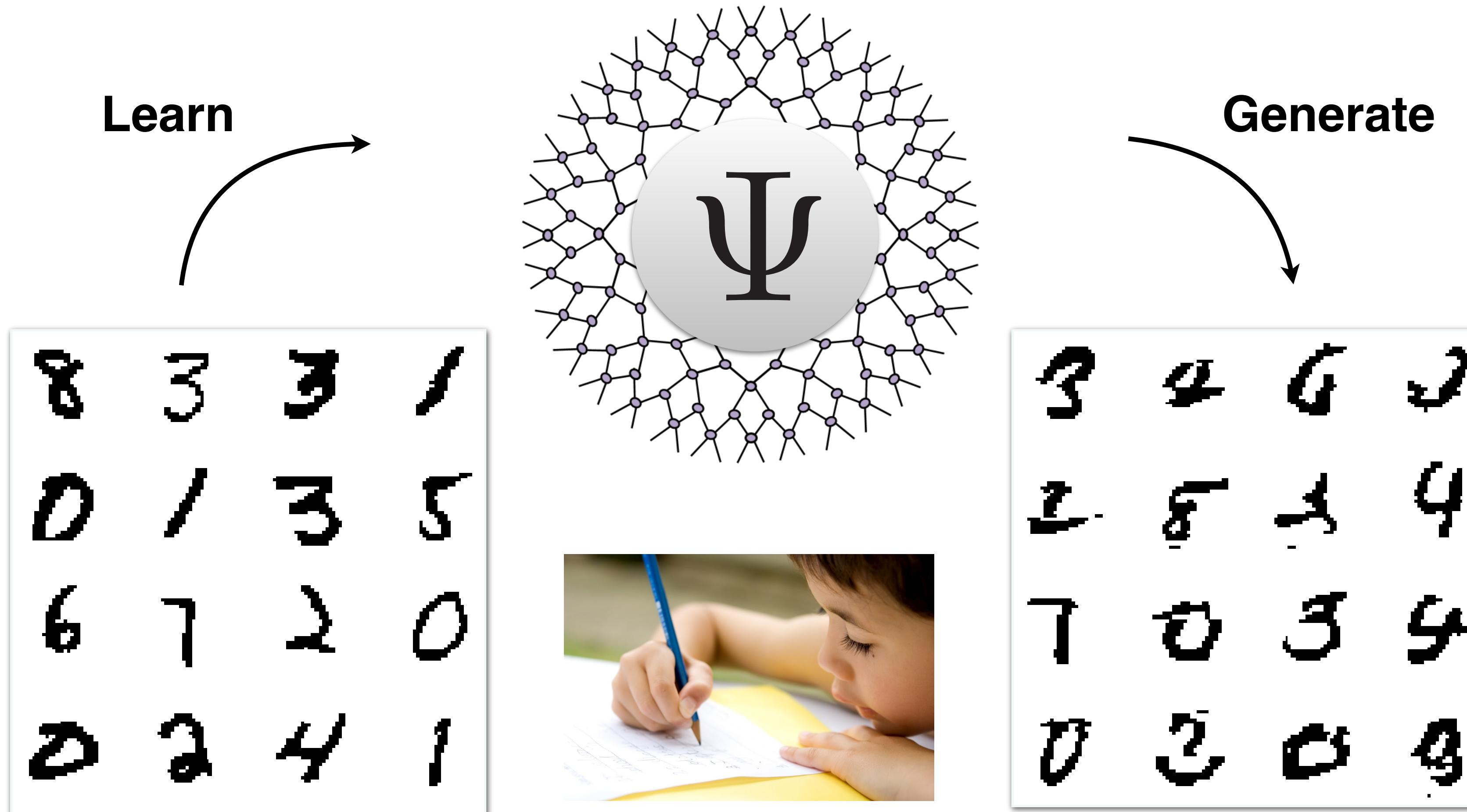
# Quantum inspired generative modeling



# Quantum inspired generative modeling



# Quantum inspired generative modeling

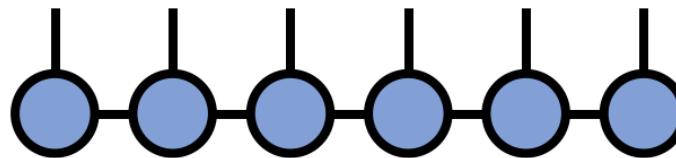


**“Teach a quantum state to write digits”**

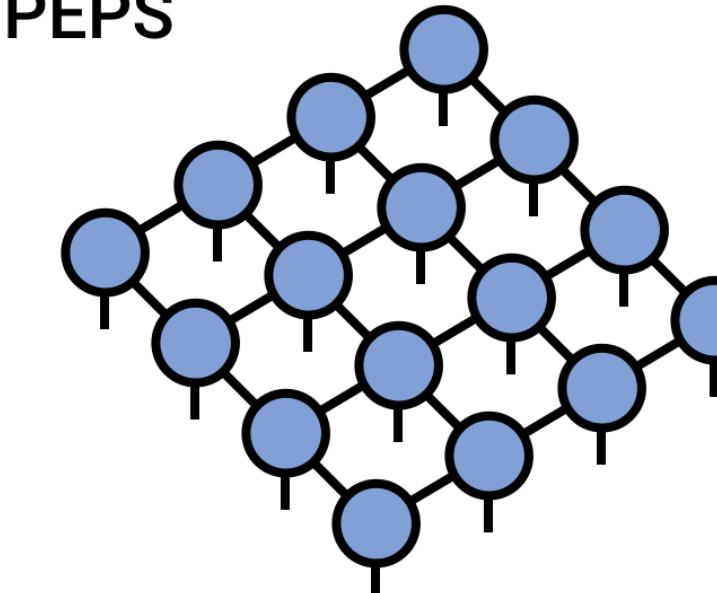
With Han, Wang, Fan, Zhang, 1709.01662, PRX ‘18

# Generative modeling using Tensor Network States

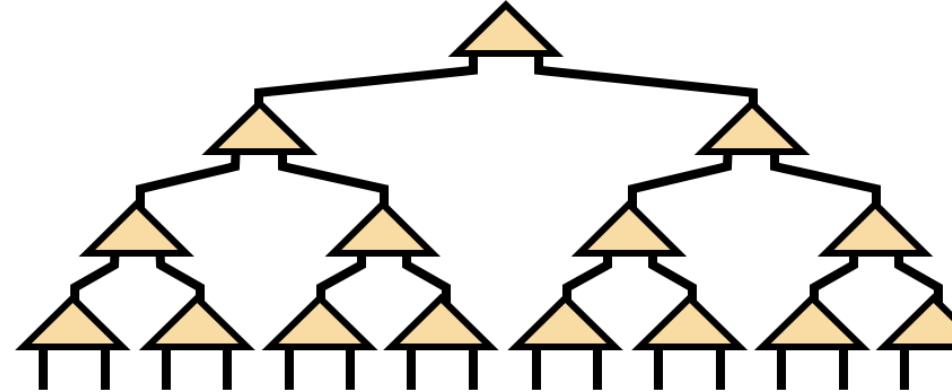
Matrix Product State /  
Tensor Train



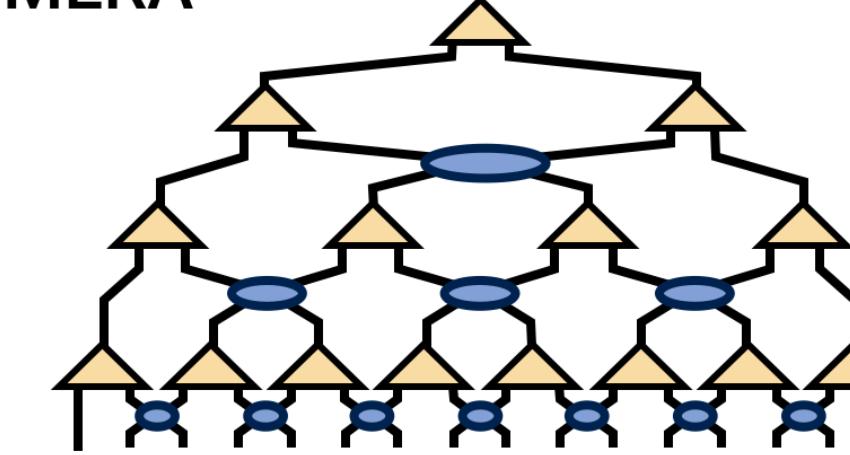
PEPS



Tree Tensor Network /  
Hierarchical Tucker



MERA



## Tensor Network Machine Learning

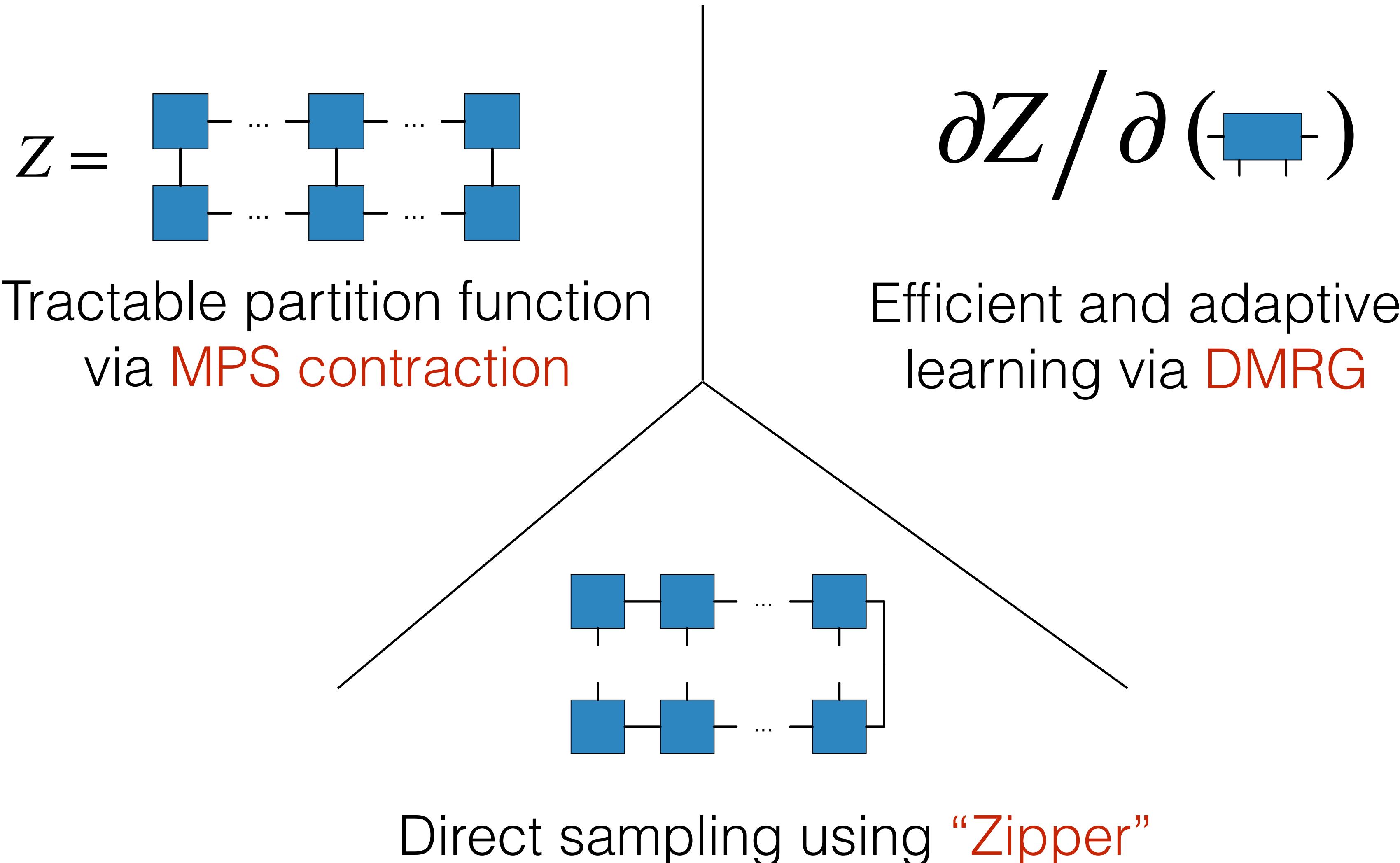
Cichocki et al 1604.05271, 1609.00893, 1708.09165...  
Stoudenmire, Schwab NIPS 2016 Liu et al 1710.04833  
Stoudenmire Q. Sci. Tech. 2018 Liu et al 1803.09111

Novikov et al 1509.06569  
Hallam et al 1711.03357  
Glasser et al 1806.05964

Kossaifi et al 1707.08308  
Gallego, Orus 1708.01525  
Pestun et al 1711.01416...

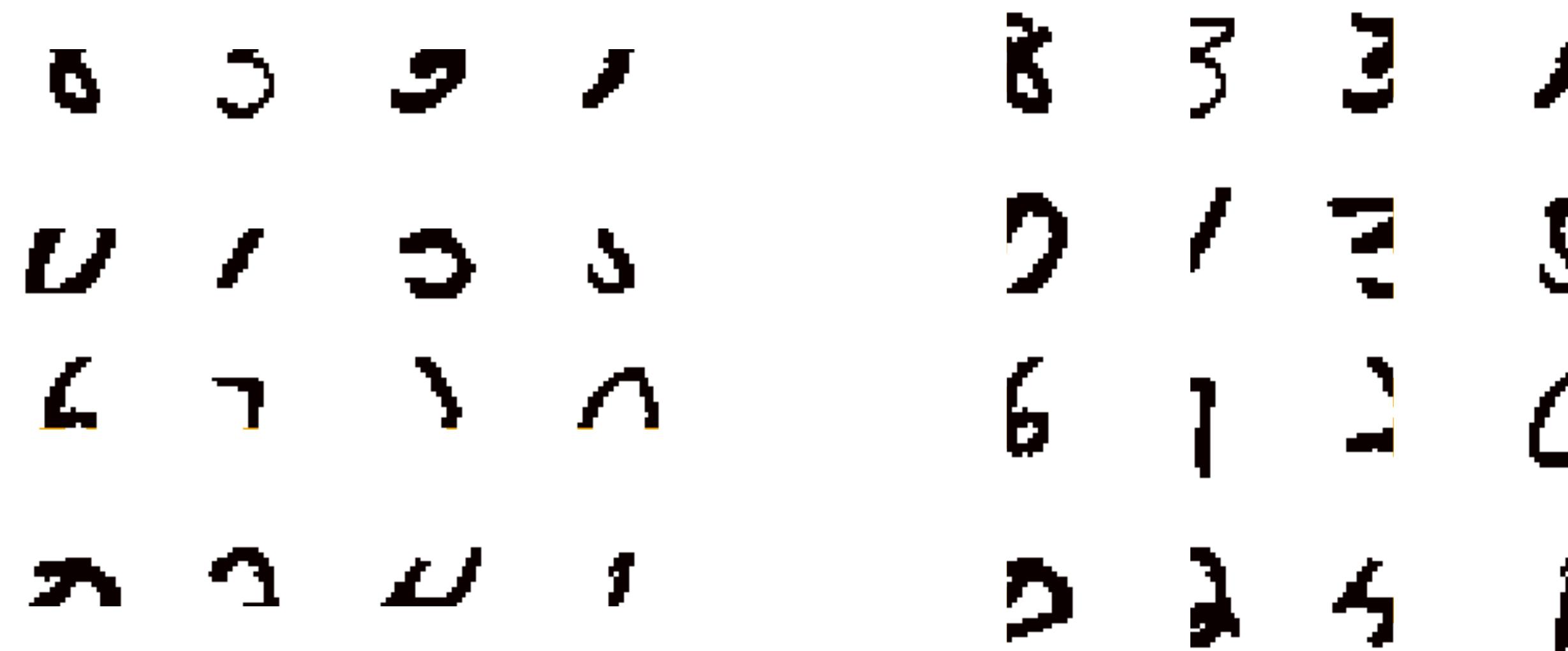
# Nice features of MPS Born Machines

Han, Wang, Fan, LW, Zhang, 1709.01662, PRX '18



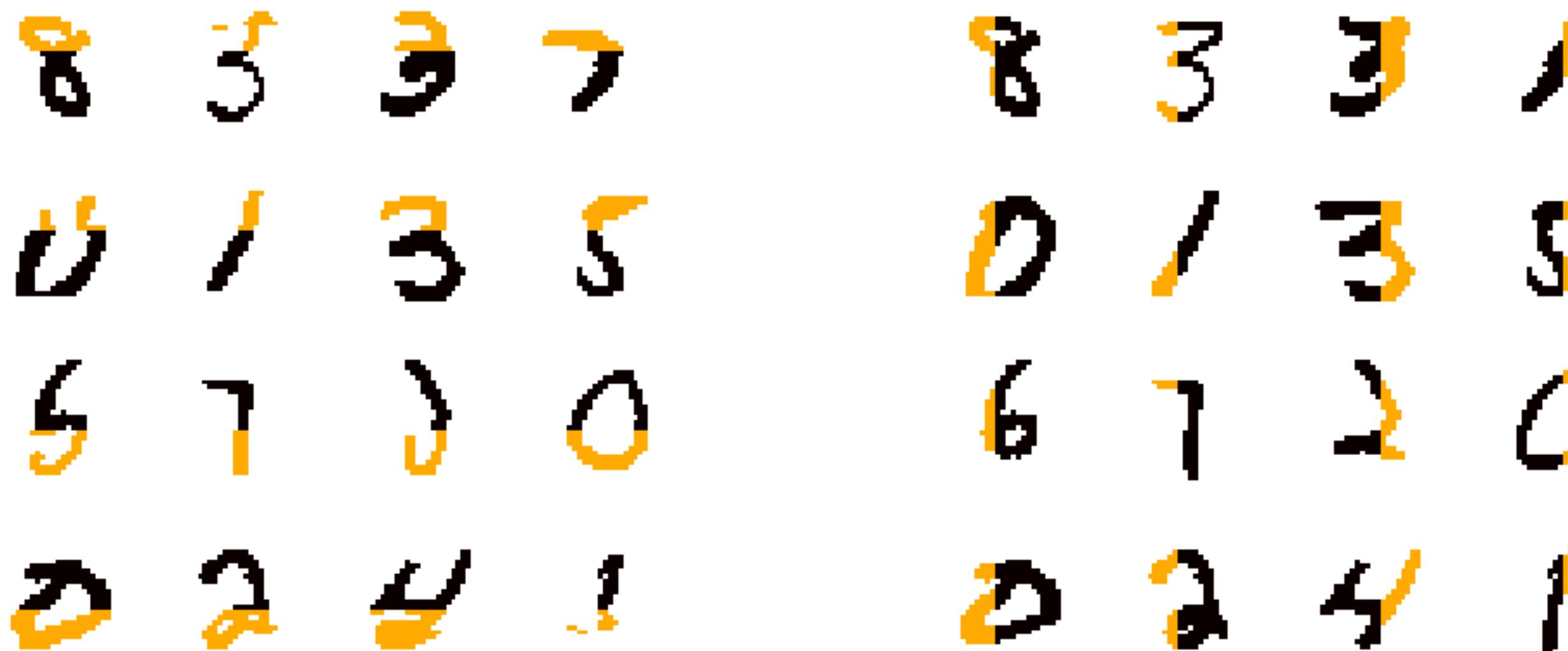
# Image Restoration

With Han, Wang, Fan, Zhang, 1709.01662, PRX '18



# Image Restoration

With Han, Wang, Fan, Zhang, 1709.01662, PRX '18

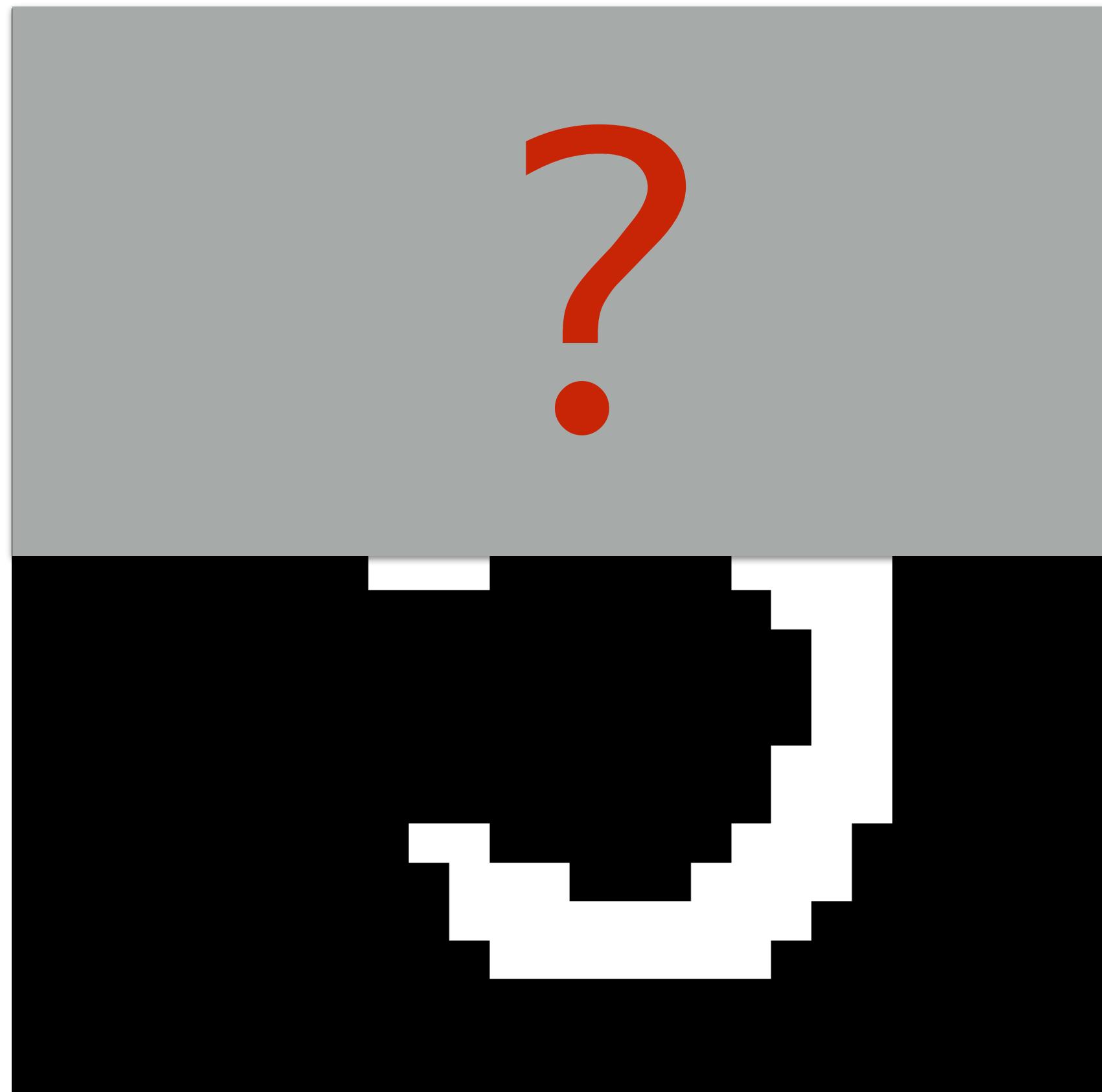


**Arbitrary order, in contrast to autoregressive models**



PixelCNN

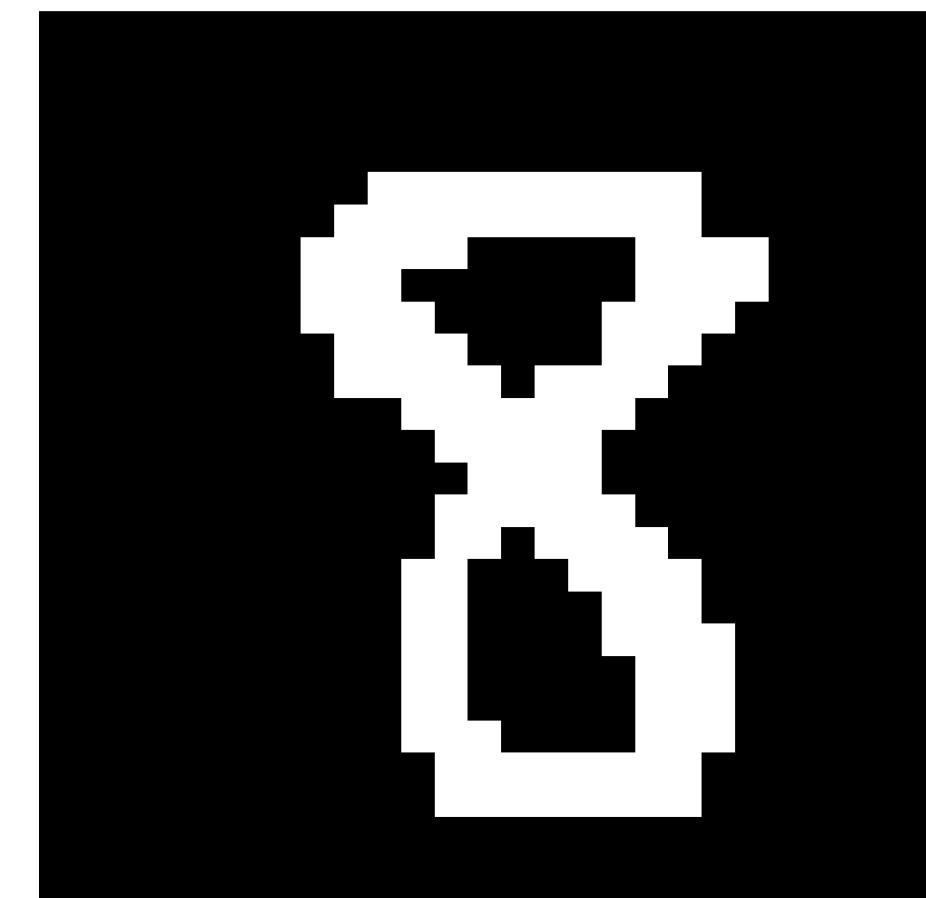
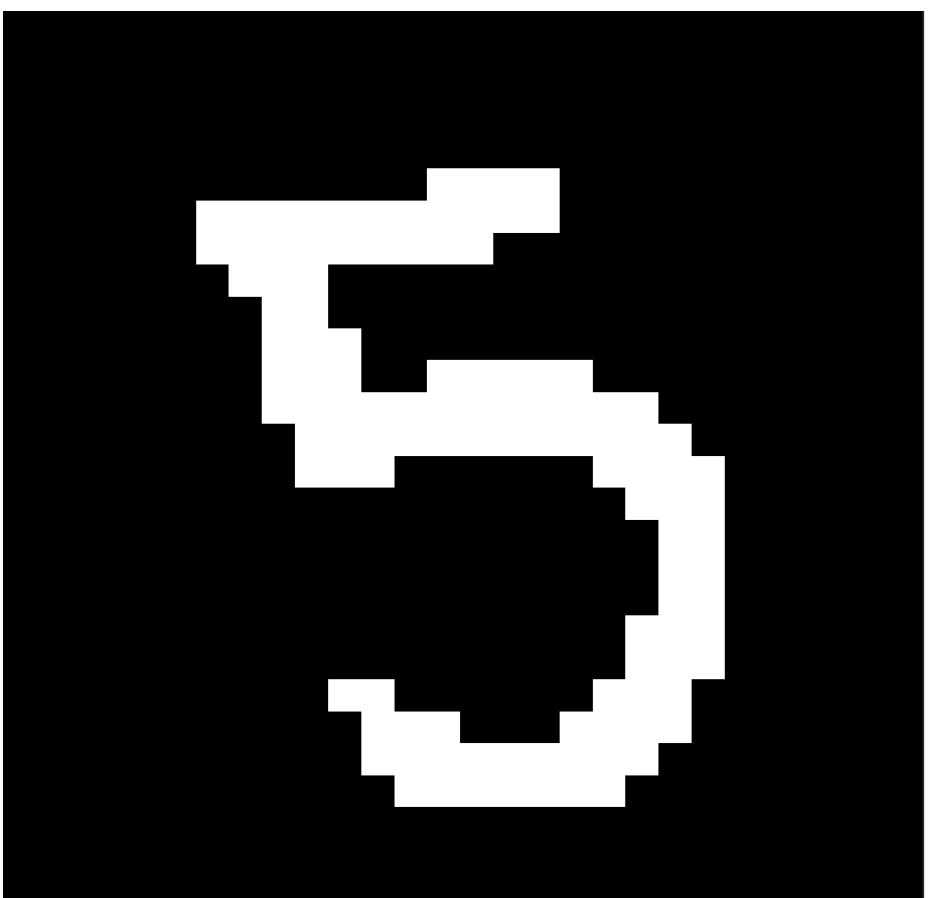
# Quantum Perspective on Deep Learning



# Quantum Perspective on Deep Learning

**Q: How to quantify our inductive biases ?**

**A: Information pattern of probability distributions**



# Quantum Perspective on Deep Learning

**Q: How to quantify our inductive biases ?**

**A: Information pattern of probability distributions**



# Quantum Perspective on Deep Learning

**Q: How to quantify our inductive biases ?**

**A: Information pattern of probability distributions**



# Quantum Perspective on Deep Learning

$$p\left(\begin{array}{|c|} \hline \text{E} \\ \hline \text{3} \\ \hline \end{array}\right) \times p\left(\begin{array}{|c|} \hline \text{3} \\ \hline \text{E} \\ \hline \end{array}\right)$$

---

$$p\left(\begin{array}{|c|} \hline \text{E} \\ \hline \text{3} \\ \hline \end{array}\right) \times p\left(\begin{array}{|c|} \hline \text{3} \\ \hline \text{E} \\ \hline \end{array}\right)$$

# Quantum Perspective on Deep Learning

## Classical mutual information

$$I = - \left\langle \ln \left\langle \frac{p(x, y') p(x', y)}{p(x', y') p(x, y)} \right\rangle_{x', y'} \right\rangle_{x, y}$$

## Quantum Renyi entanglement entropy

$$S = - \ln \left\langle \left\langle \frac{\Psi(x, y') \Psi(x', y)}{\Psi(x', y') \Psi(x, y)} \right\rangle_{x', y'} \right\rangle_{x, y}$$

**Striking similarity implies common inductive bias**

- + Quantitative & interpretable approaches
- + Principled structure design & learning

Cheng, Chen, LW,  
1712.04144, Entropy '18

# DEEP LEARNING AND QUANTUM ENTANGLEMENT: FUNDAMENTAL CONNECTIONS WITH IMPLICATIONS TO NETWORK DESIGN

**Yoav Levine, David Yakira, Nadav Cohen & Amnon Shashua**

The Hebrew University of Jerusalem

{yoavlevine, davidyakira, cohennadav, shashua}@cs.huji.ac.il

## ABSTRACT

Formal understanding of the inductive bias behind deep convolutional networks, i.e. the relation between the network’s architectural features and the functions it is able to model, is limited. In this work, we establish a fundamental connection between the fields of quantum physics and deep learning, and use it for obtaining novel theoretical observations regarding the inductive bias of convolutional networks. Specifically, we show a structural equivalence between the function realized by a convolutional arithmetic circuit (ConvAC) and a quantum many-body wave function, which facilitates the use of quantum entanglement measures as quantifiers of a deep network’s expressive ability to model correlations. Furthermore, the construction of a deep ConvAC in terms of a quantum Tensor Network is enabled. This allows us to perform a graph-theoretic analysis of a convolutional network, tying its expressiveness to a min-cut in its underlying graph. We demonstrate a practical outcome in the form of a direct control over the inductive bias via the number of channels (width) of each layer. We empirically validate our findings on standard convolutional networks which involve ReLU activations and max pooling. The description of a deep convolutional network in well-defined graph-theoretic tools and the structural connection to quantum entanglement, are two interdisciplinary bridges that are brought forth by this work.

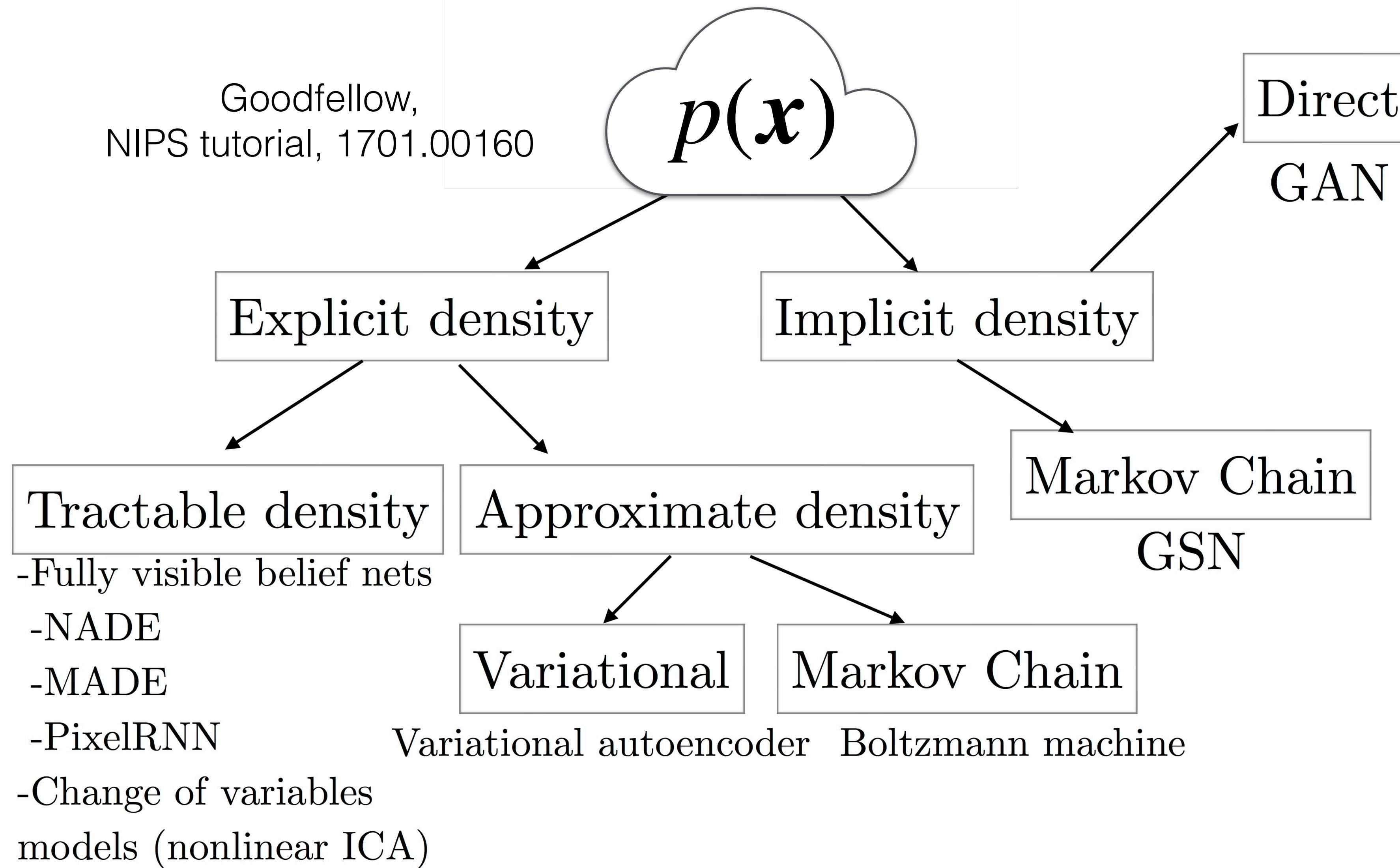
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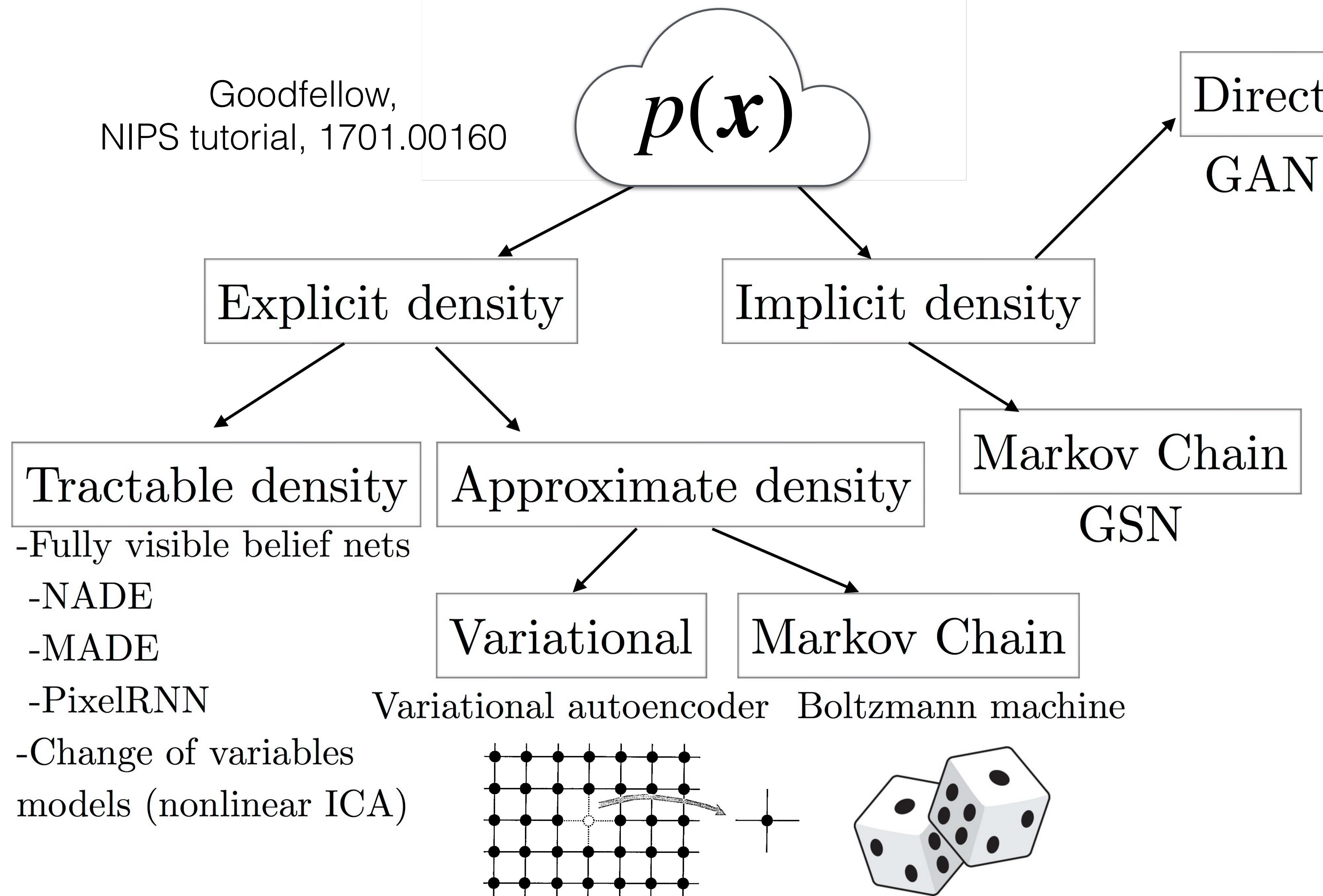


# Physics genes of generative models

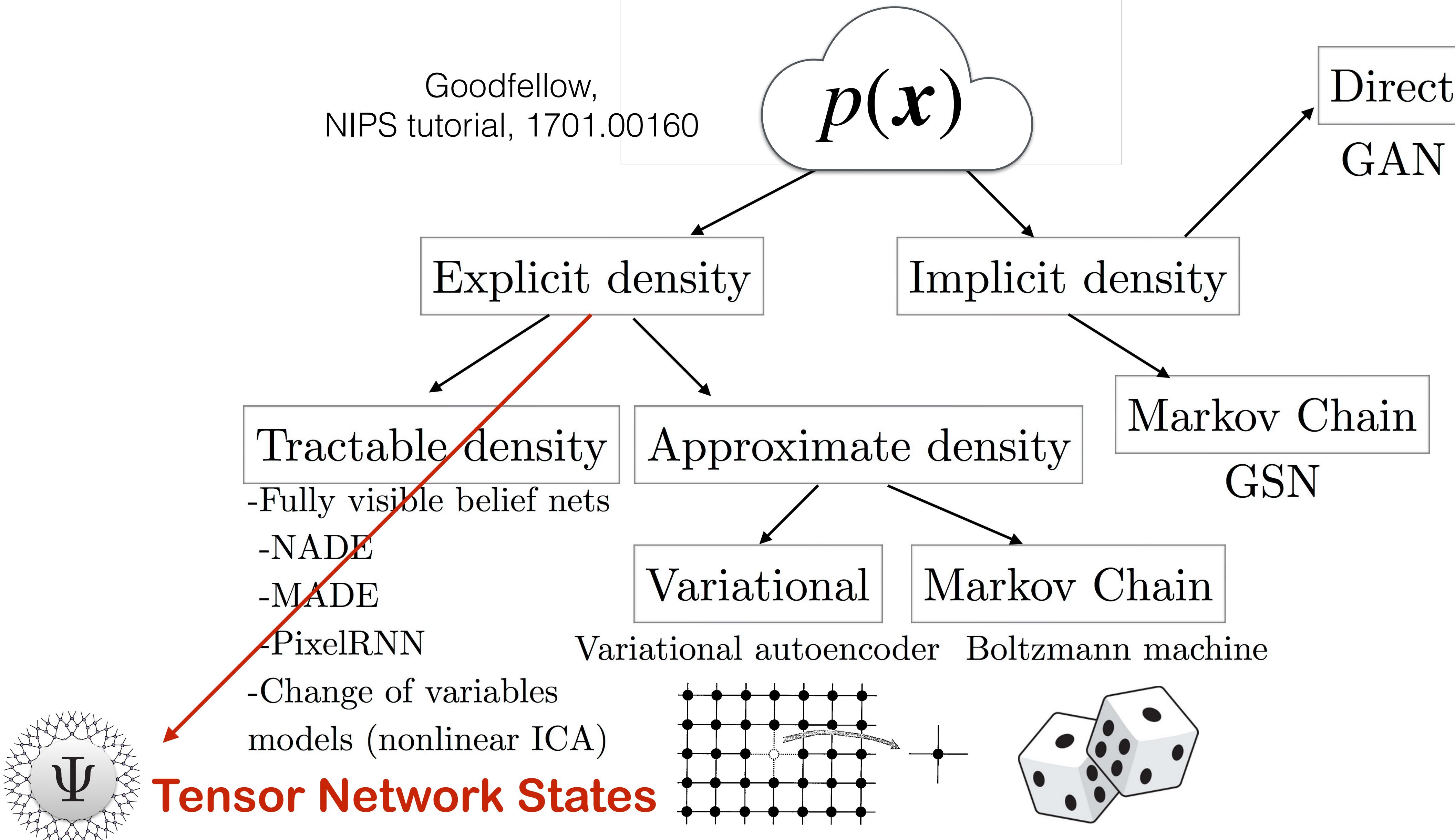


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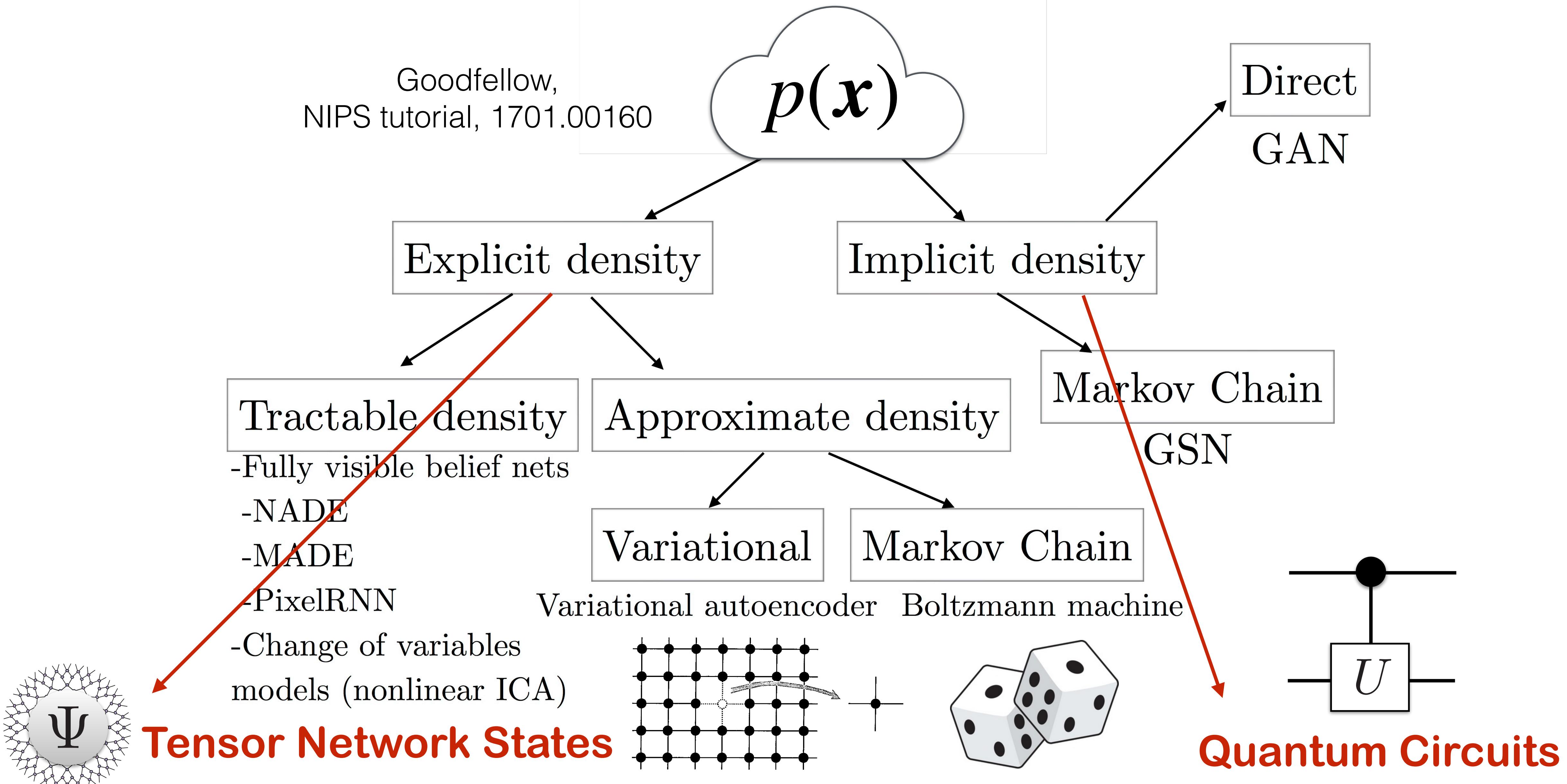
Goodfellow,  
NIPS tutorial, 1701.00160



# Physics genes of generative models

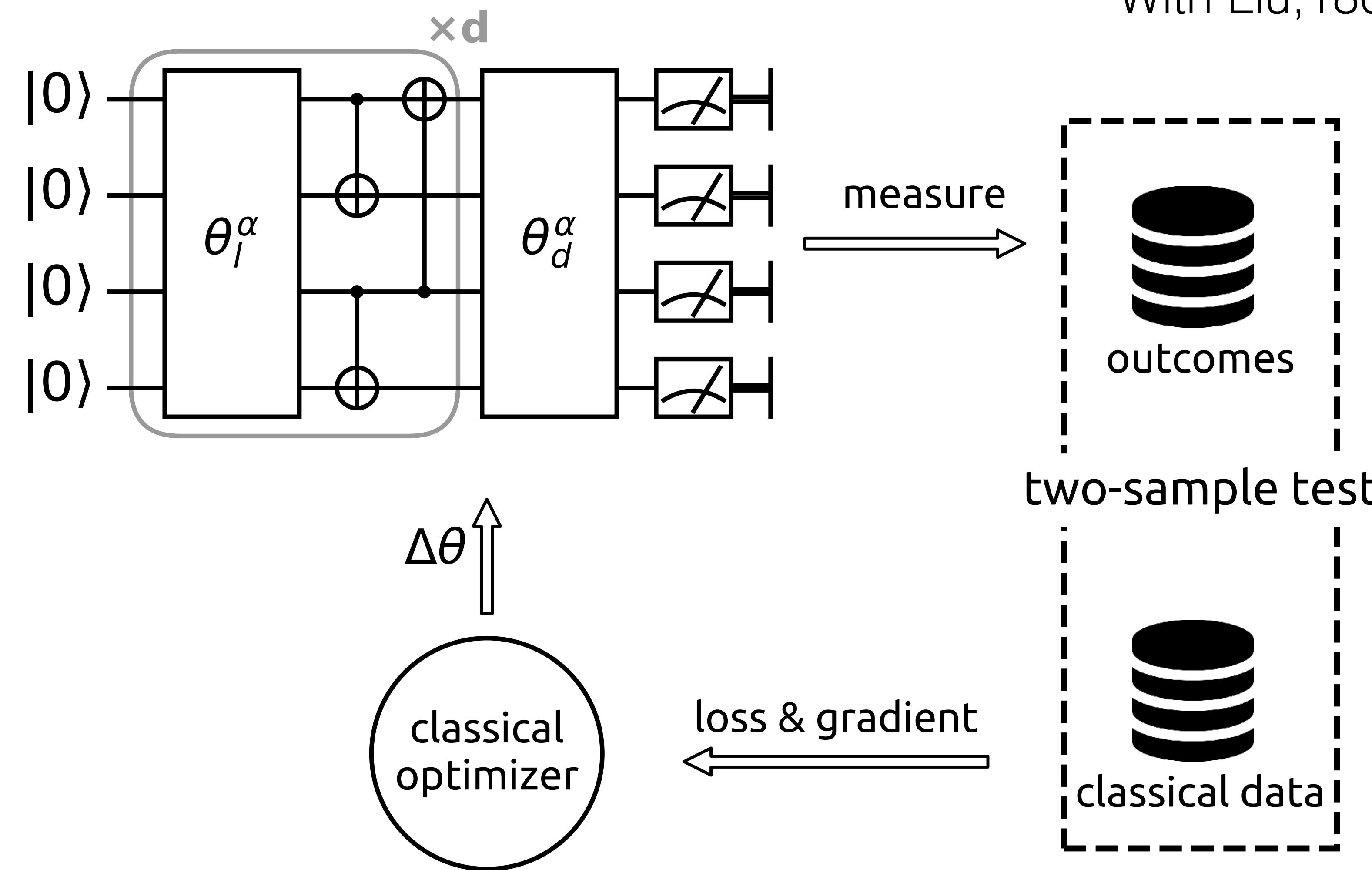


# Physics genes of generative models



# Quantum Circuit Born Machine

With Liu, 1804.04168, PRA '18

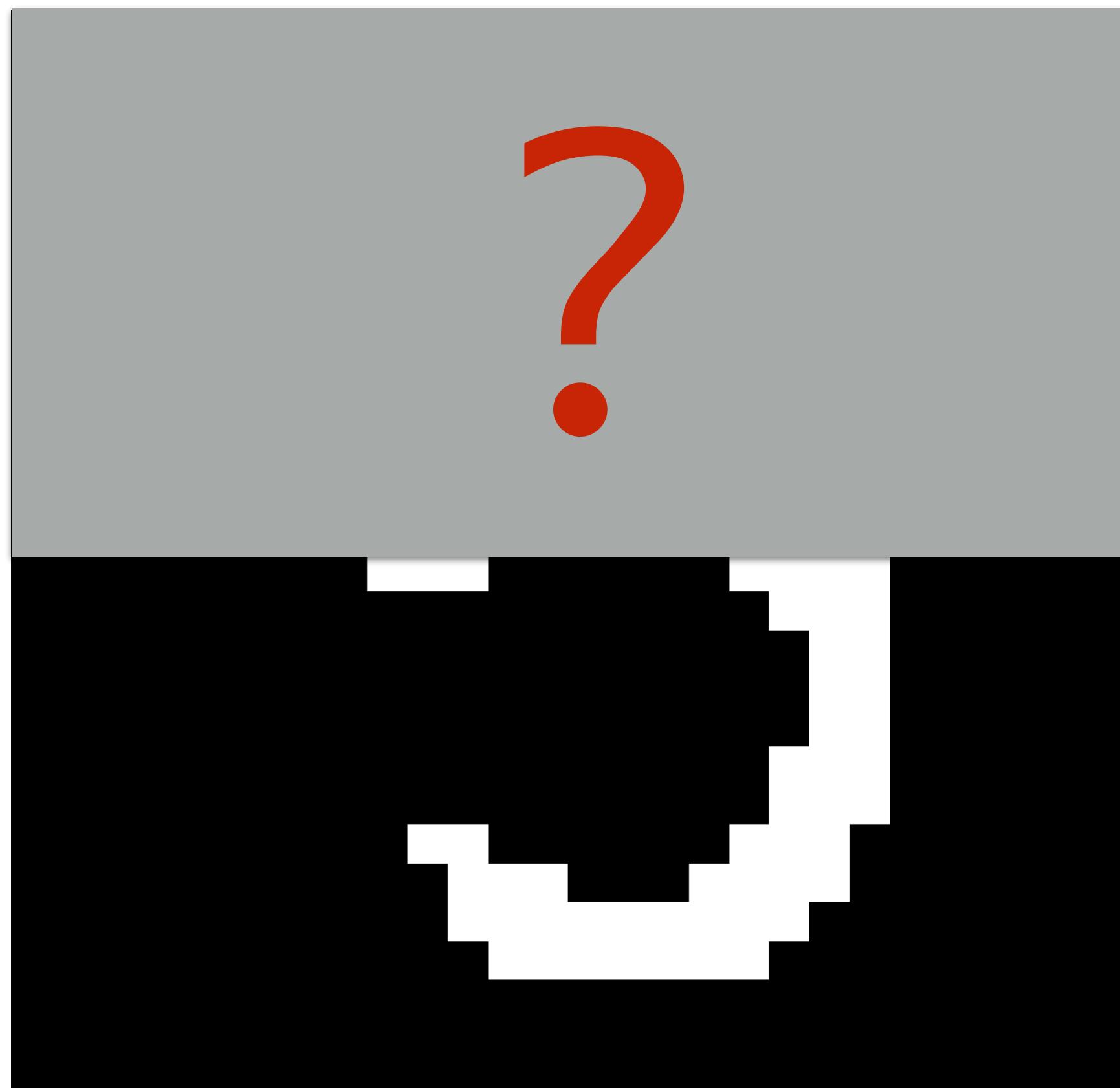


Train the quantum circuit as a probabilistic generative model

Quantum sampling complexity underlines the “quantum supremacy”

# Quantum Inference

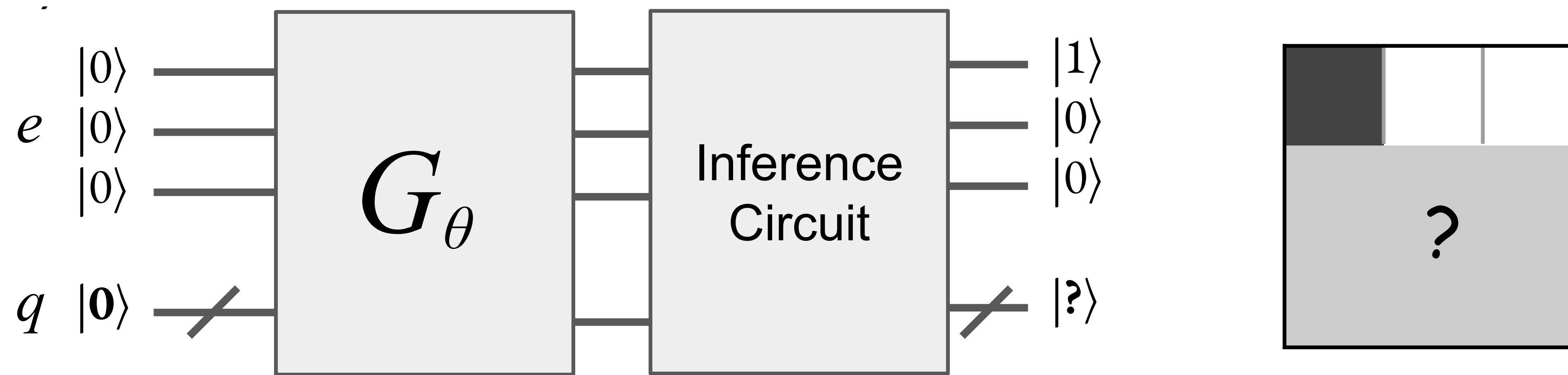
p(upper | lower)



# Quantum Inference

With Zeng, Wu, Liu, Hu, 1808.03425

Cf Low and Chuang, PRA '14



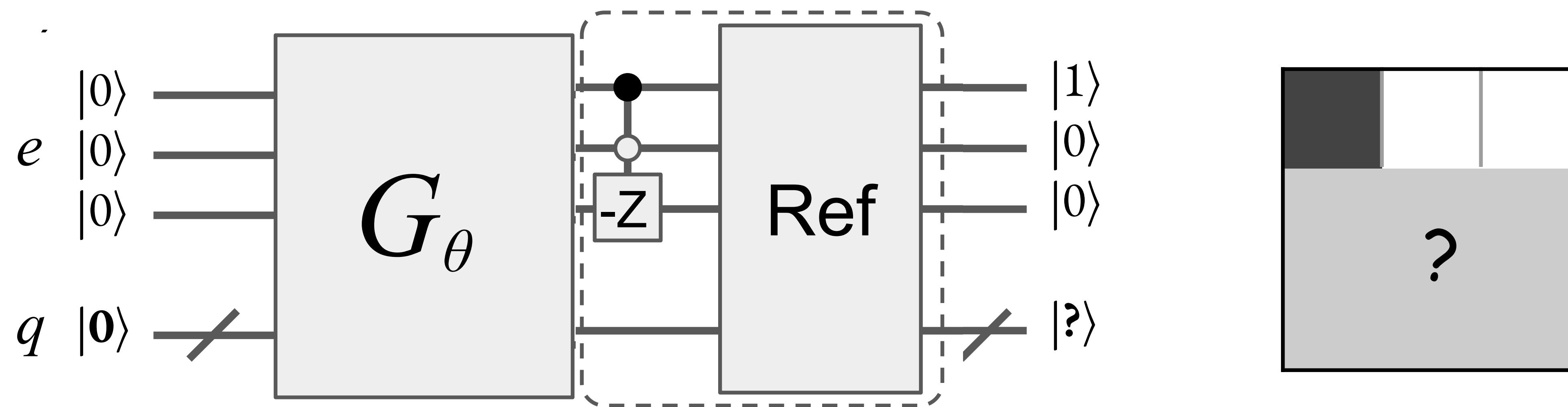
Accelerated quantum inference via Grover search

# Quantum Inference

With Zeng, Wu, Liu, Hu, 1808.03425

Grover Operator

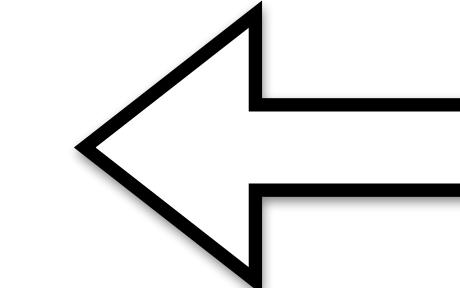
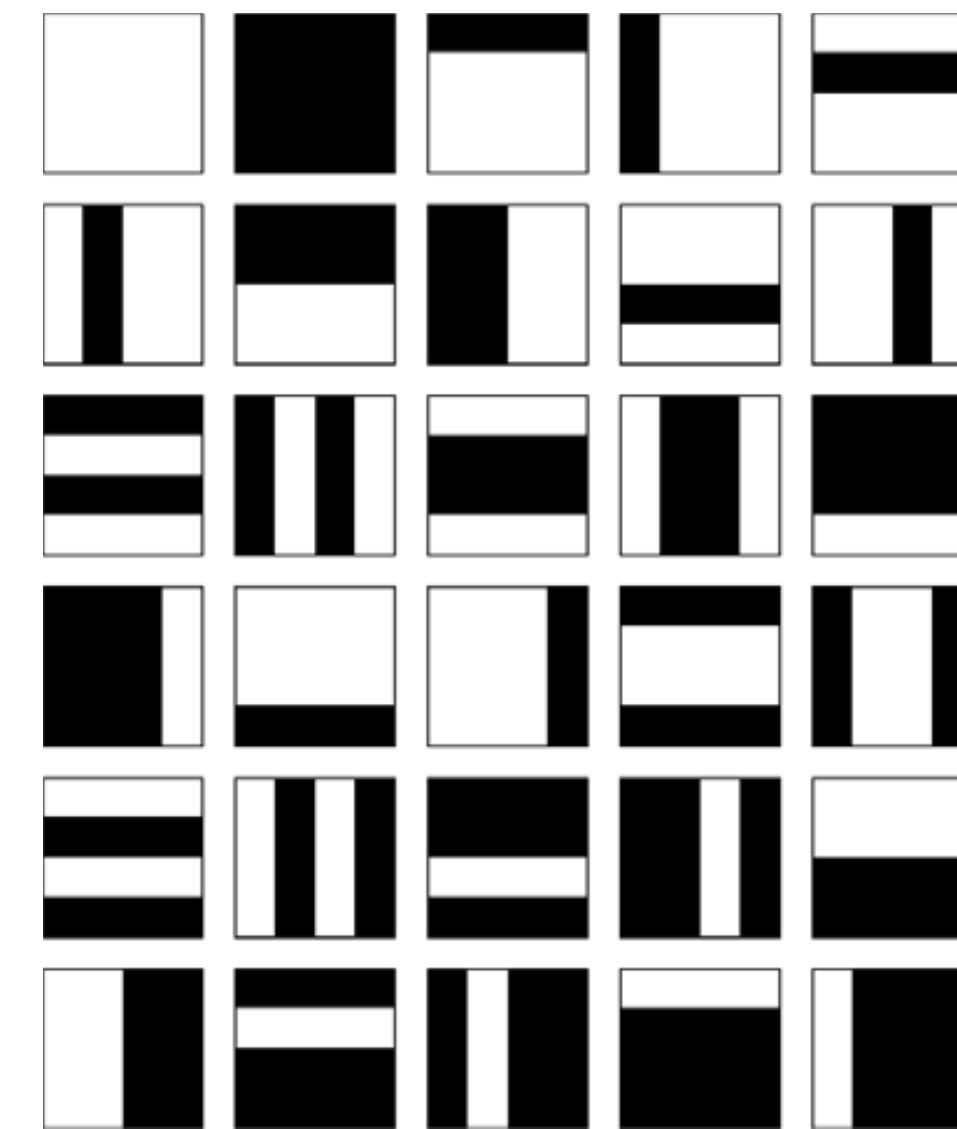
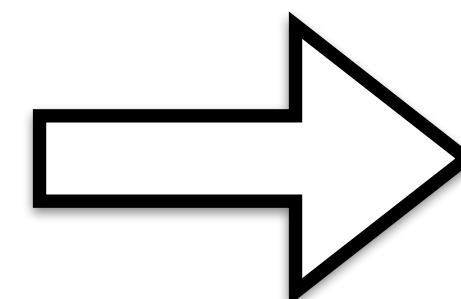
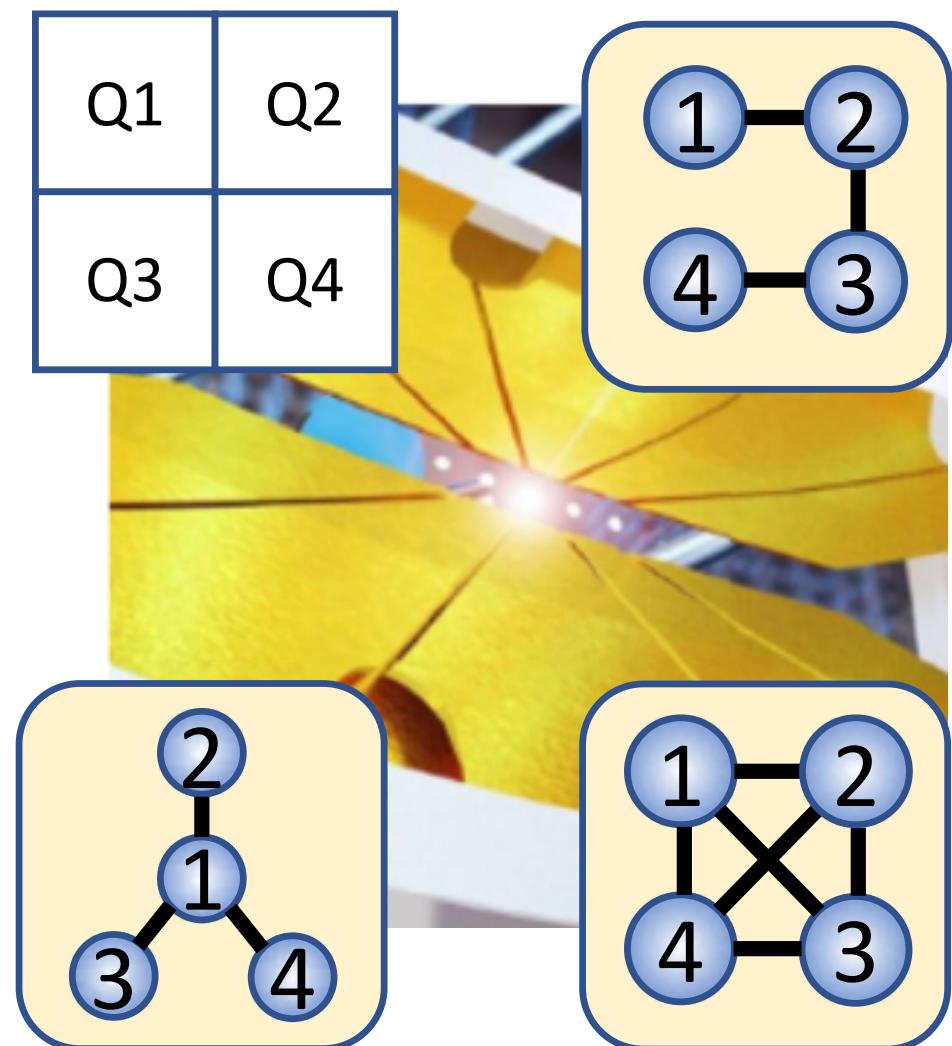
Cf Low and Chuang, PRA '14



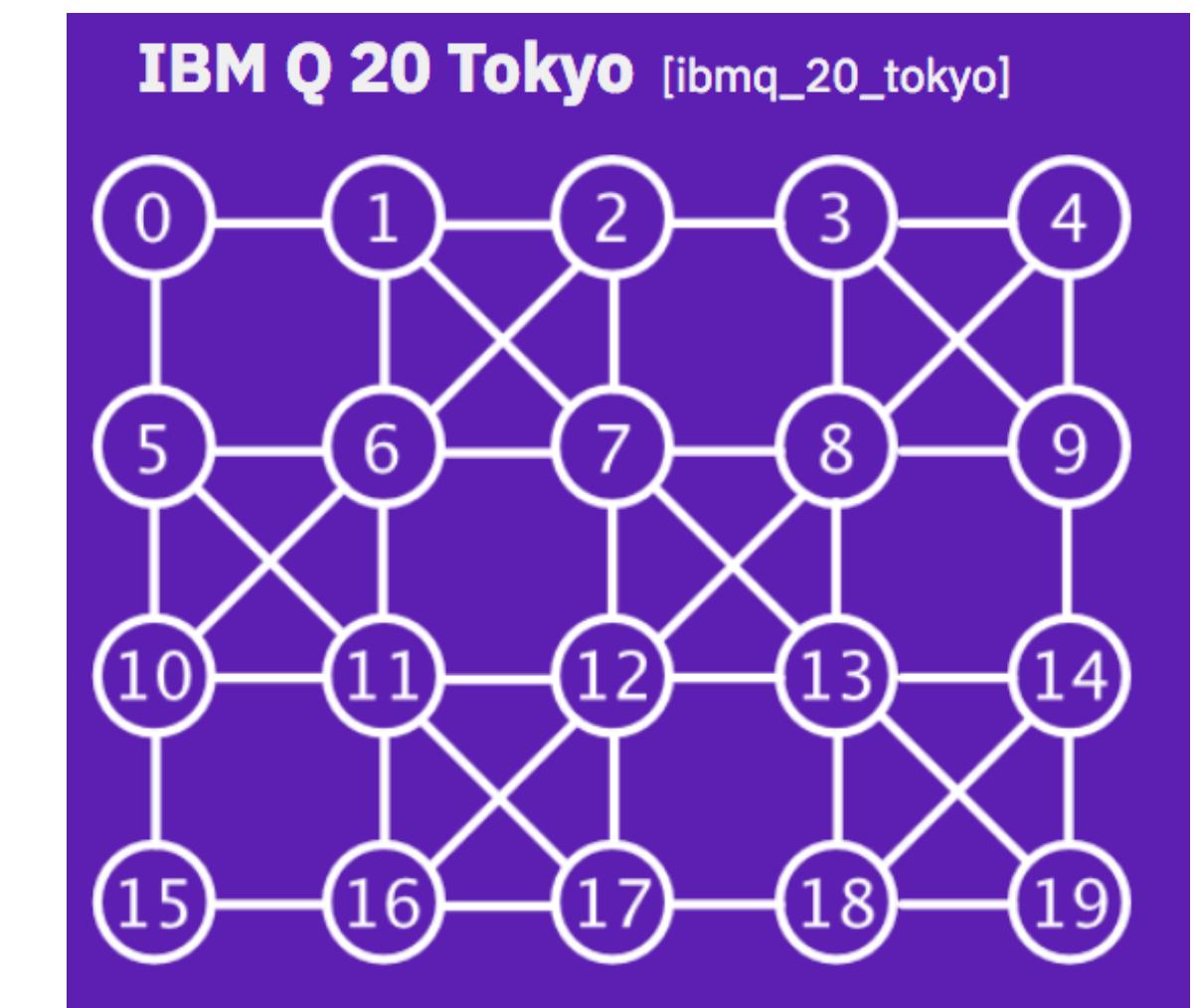
Accelerated quantum inference via Grover search

# QCBM Experiments

JQI+IonQ+UCL+Cambridge Q+...  
1801.07686, 1812.08862



Oak Ridge, 1811.09905



“Bars-and-Stripes”

Han et al, 1709.01662, PRX '18  
cf Mackay's book “Information  
Theory, Inference, and Learning”

**Generative modeling now becomes a calibration score for quantum circuits**

# Key questions to the future of QCBM

①

## Is it really useful?

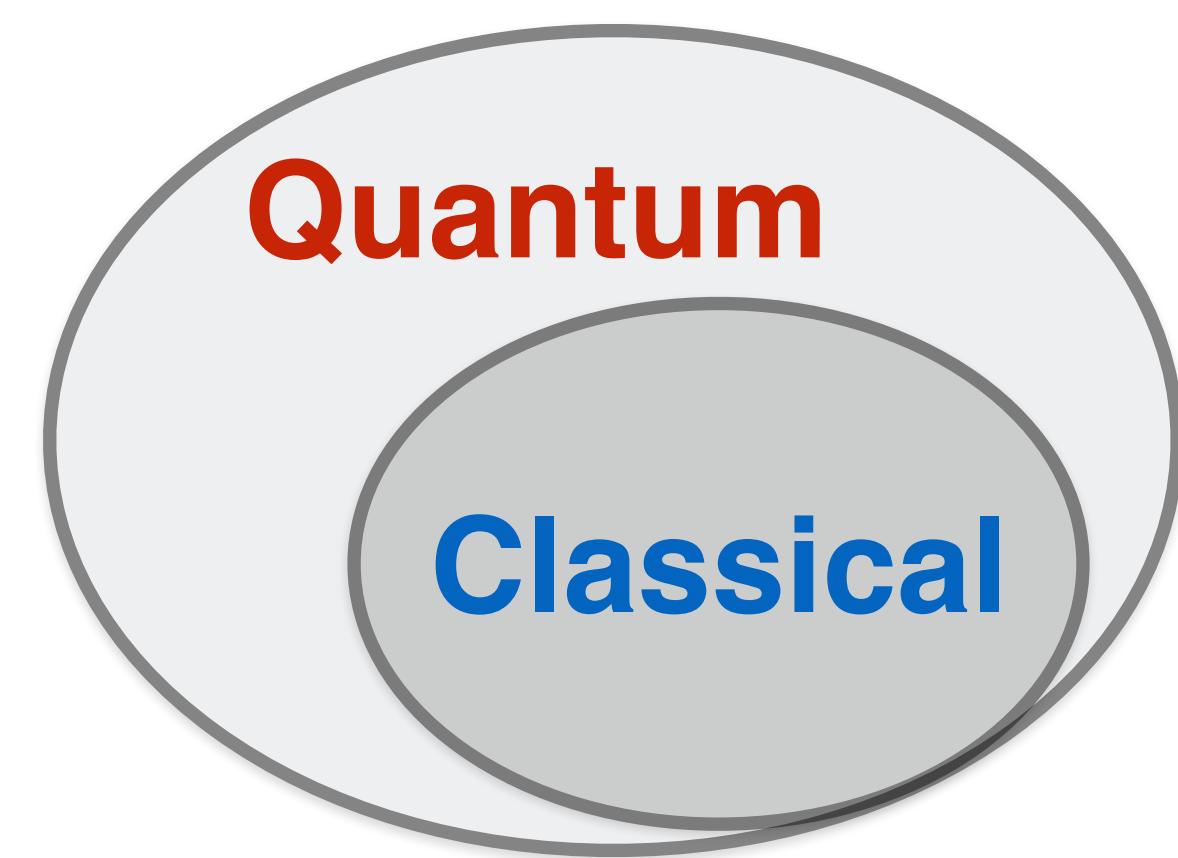
A killer problem distribution where quantum **really helps**

②

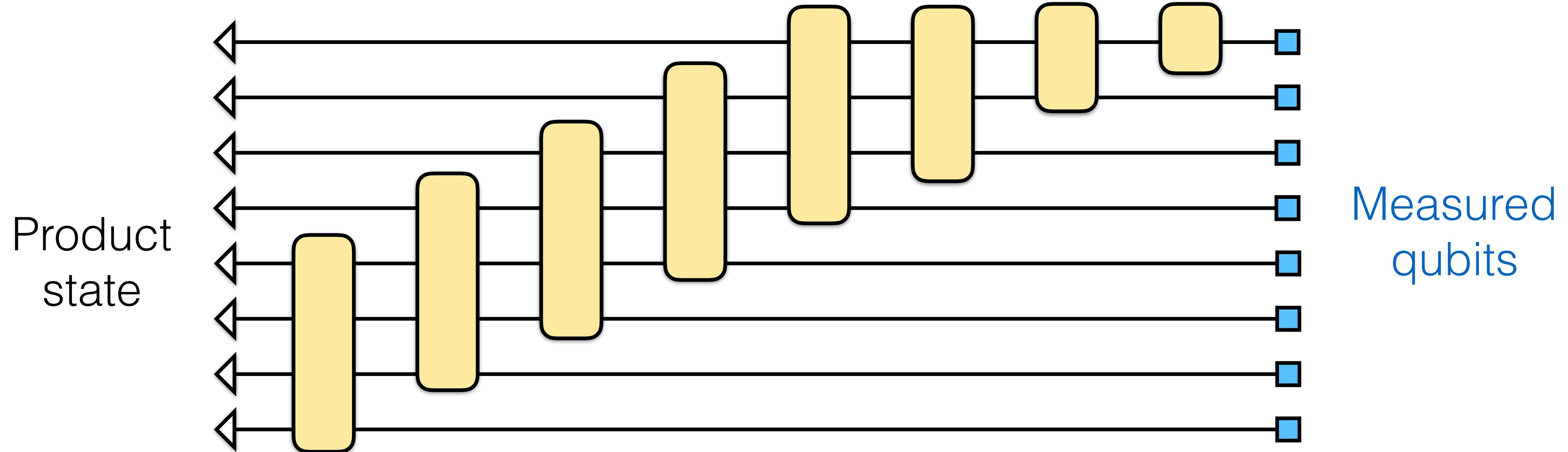
## Scale it up

- Algorithmically saving qubit number
- Quantum circuit architecture design & learning
- Differentiable learning of quantum circuits

Probability space



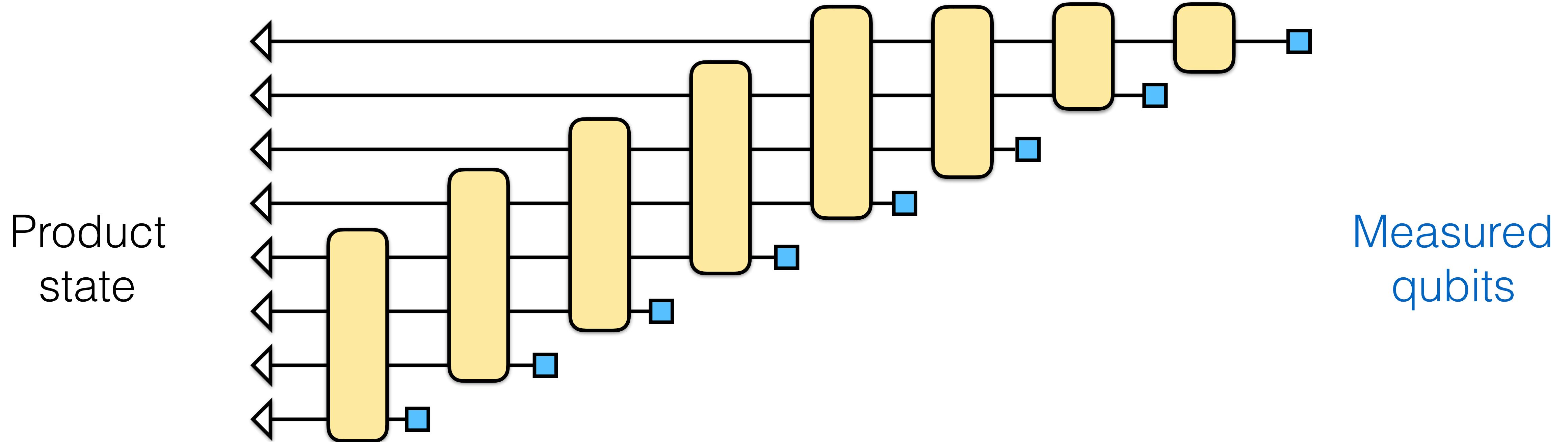
# Architecture: Qubit efficient scheme



Huggins, Patel, Whaley, Stoudenmire, 1803.11537  
see also Cramer et al, Nat. Comm. 2010

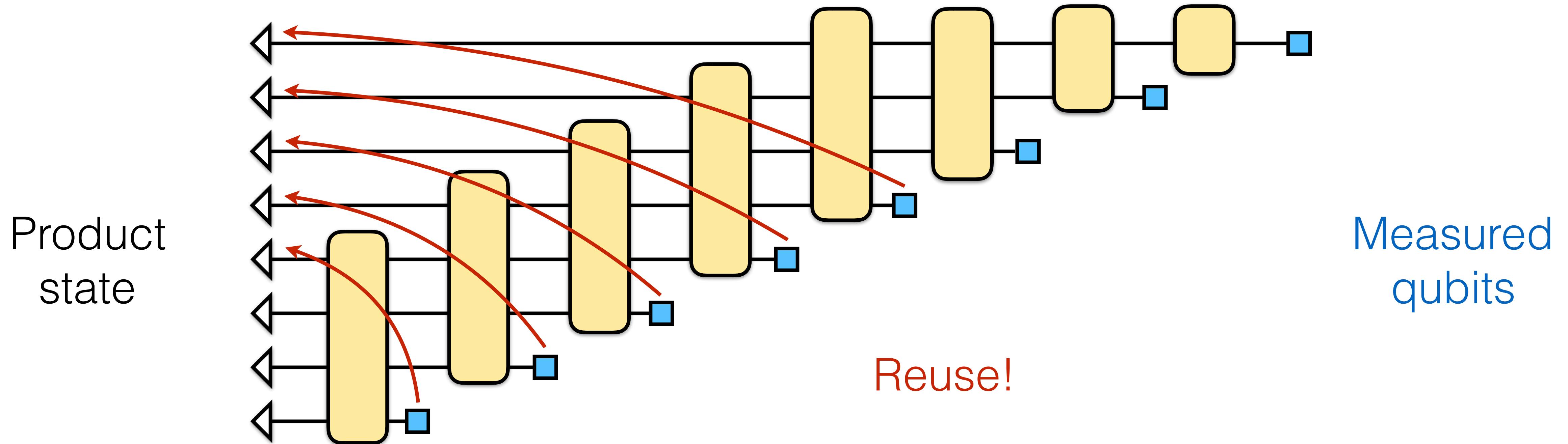
**Tensor network inspired quantum circuit architecture**

# Architecture: Qubit efficient scheme



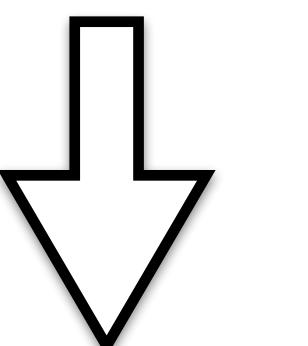
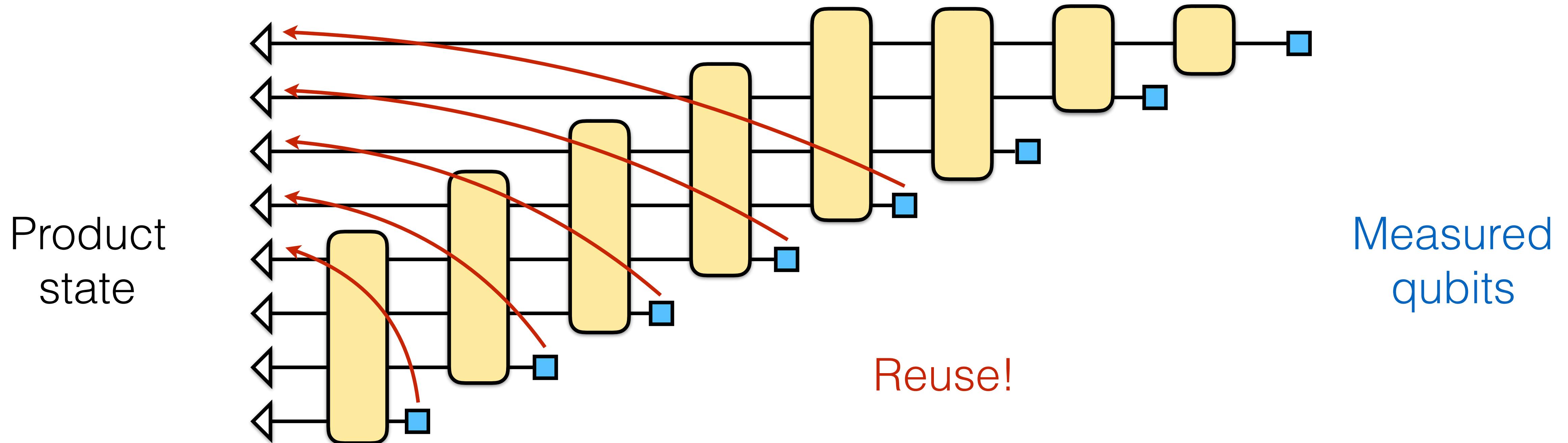
Huggins, Patel, Whaley, Stoudenmire, 1803.11537  
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# Architecture: Qubit efficient scheme

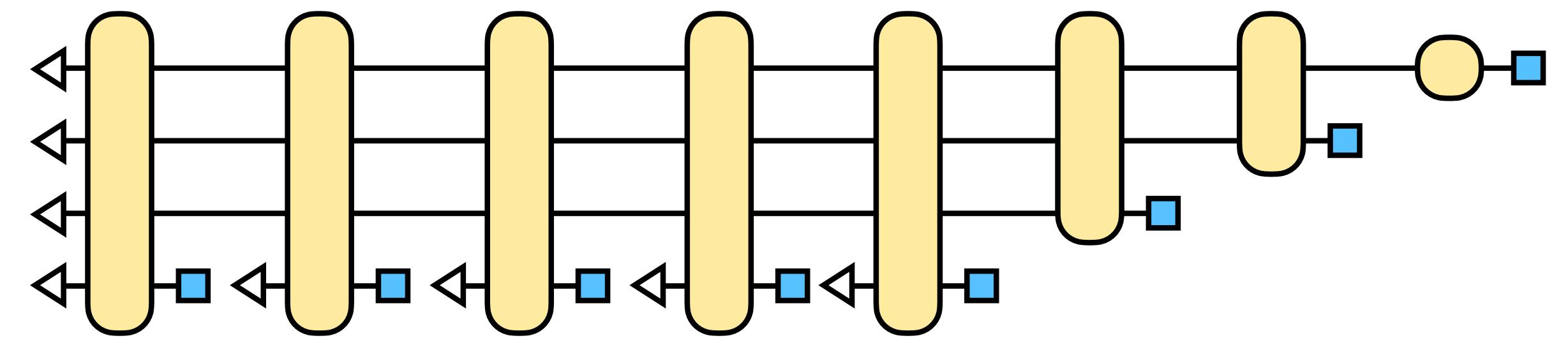


Huggins, Patel, Whaley, Stoudenmire, 1803.11537  
see also Cramer et al, Nat. Comm. 2010

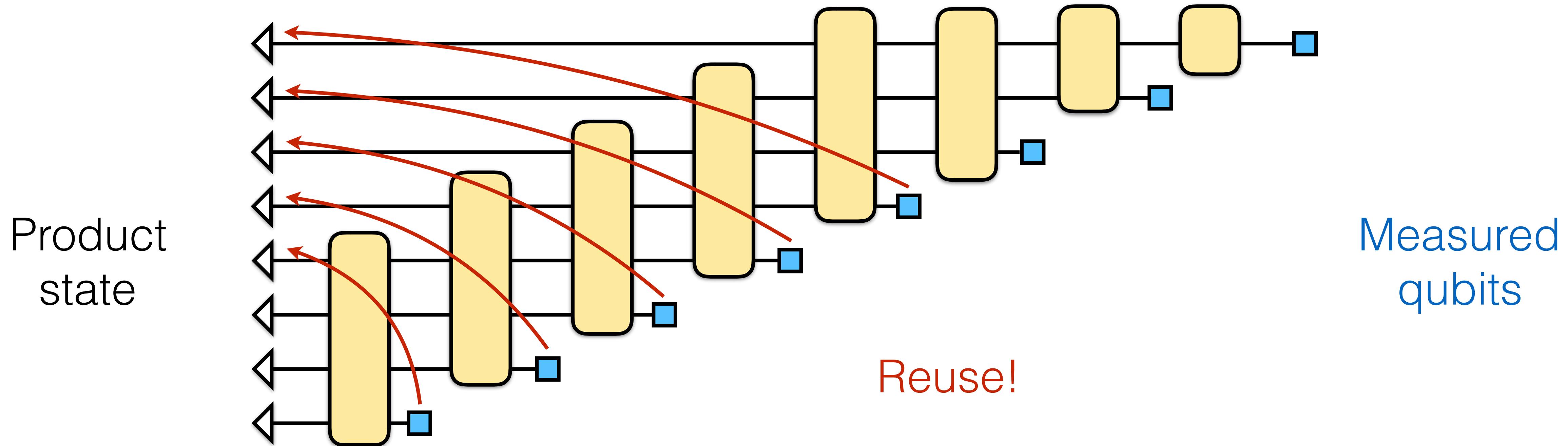
# Architecture: Qubit efficient scheme



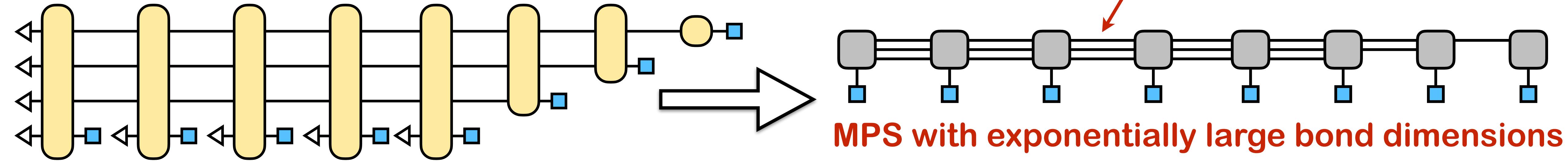
Huggins, Patel, Whaley, Stoudenmire, 1803.11537  
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# Architecture: Qubit efficient scheme



↓  
Huggins, Patel, Whaley, Stoudenmire, 1803.11537  
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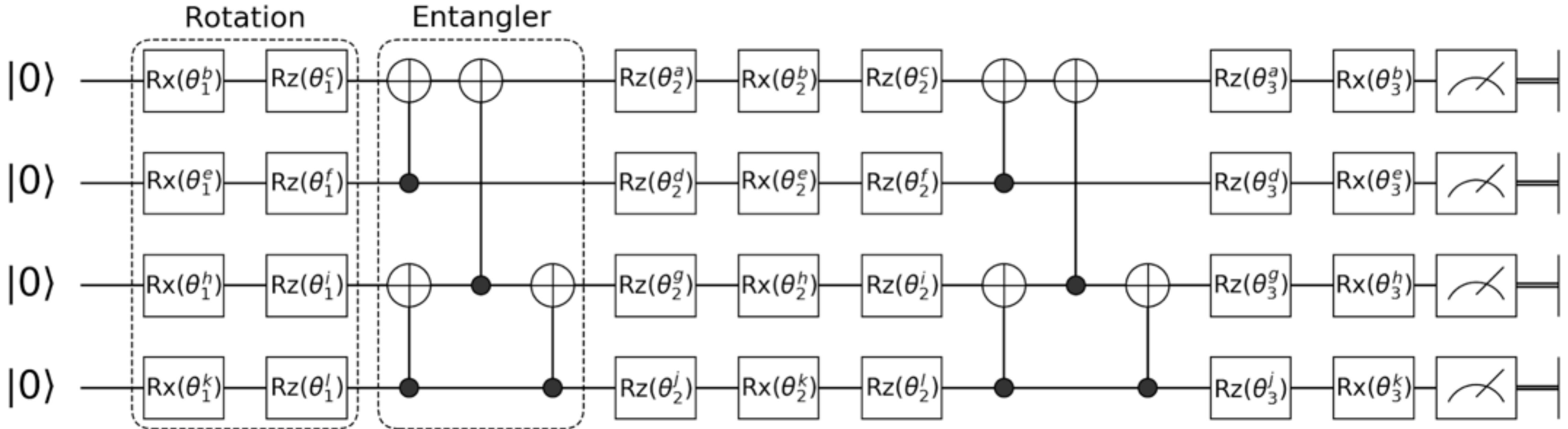


# Training: differentiable learning



**Gradient based optimization is the engine of deep learning**

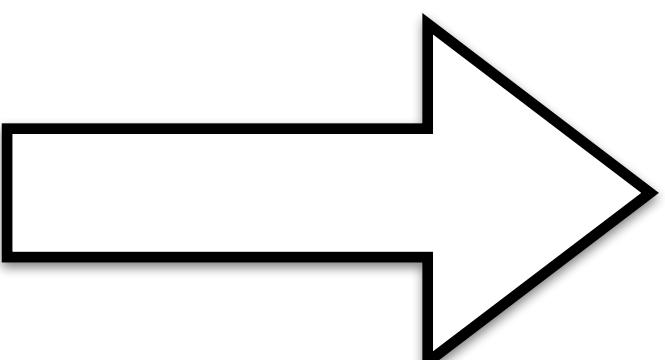
# Differentiable quantum circuits



Parametrized gate of the form

$$e^{-\frac{i\theta}{2}\Sigma} \text{ with } \Sigma^2 = 1$$

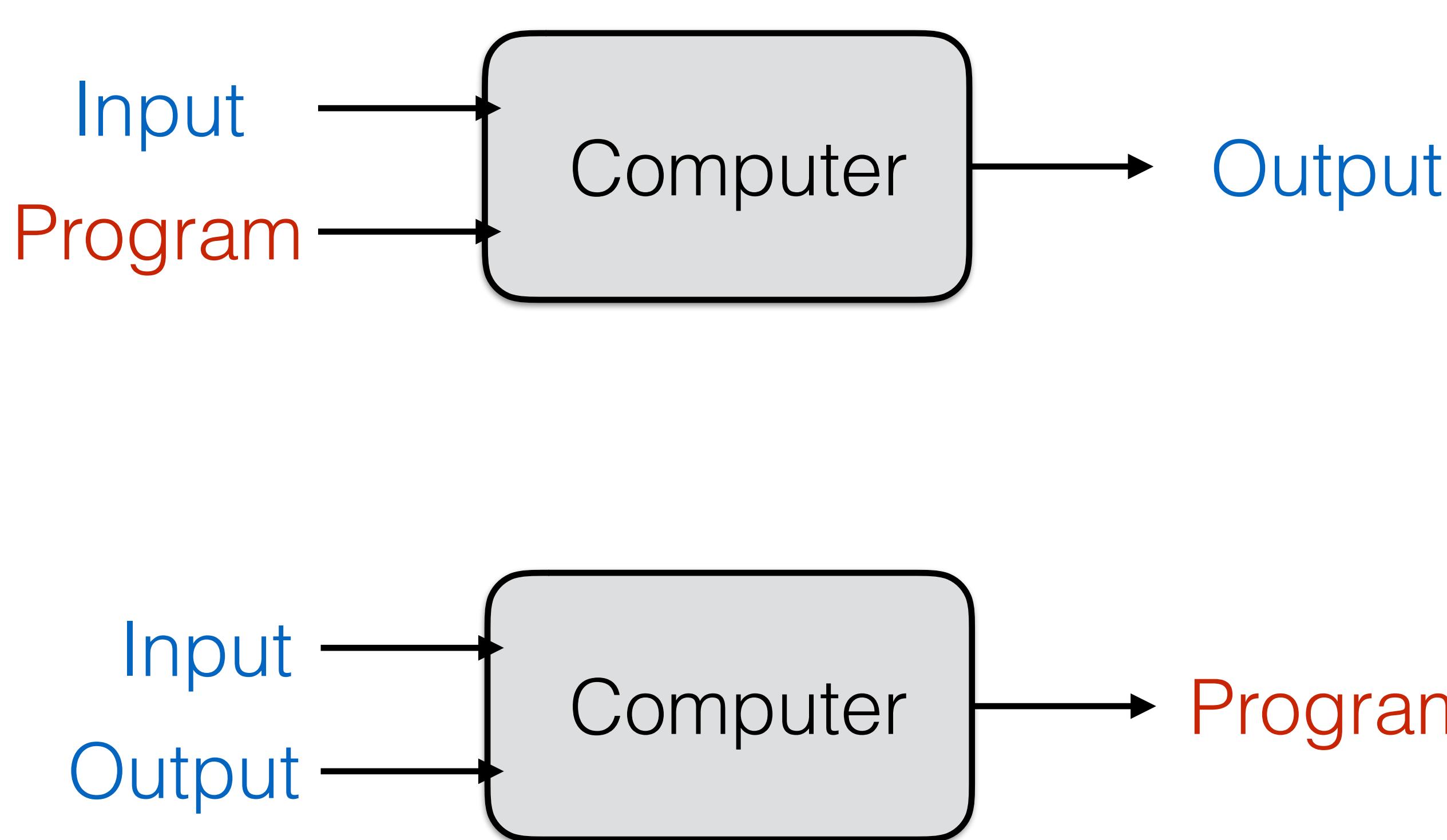
eg, X, Y, Z, CNOT, SWAP...



With Liu 1804.04168, c.f. Li et al 1608.00677  
Mitarai et al 1803.00745 Xanadu 1811.04968

$$\nabla \langle O \rangle_\theta = (\langle O \rangle_{\theta+\pi/2} - \langle O \rangle_{\theta-\pi/2})/2$$

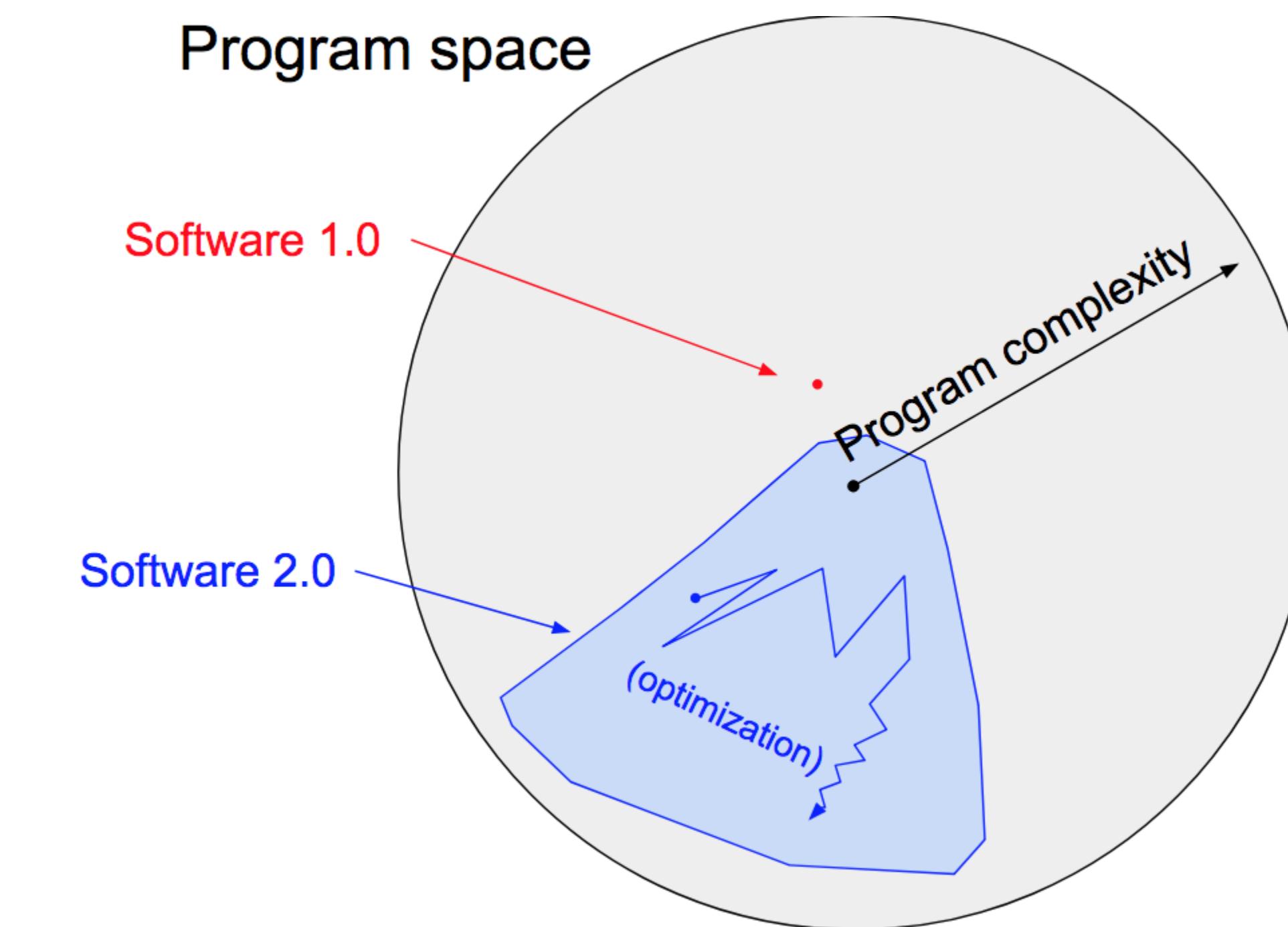
# Differentiable Programming



**Andrej Karpathy**

Director of AI at Tesla. Previously Research Scientist at OpenAI and PhD student at Stanford. I like to train deep neural nets on large datasets.

<https://medium.com/@karpathy/software-2-0-a64152b37c35>



**Writing software 2.0 by gradient search in the program space**

# Differentiable Programming

## Benefits of Software 2.0

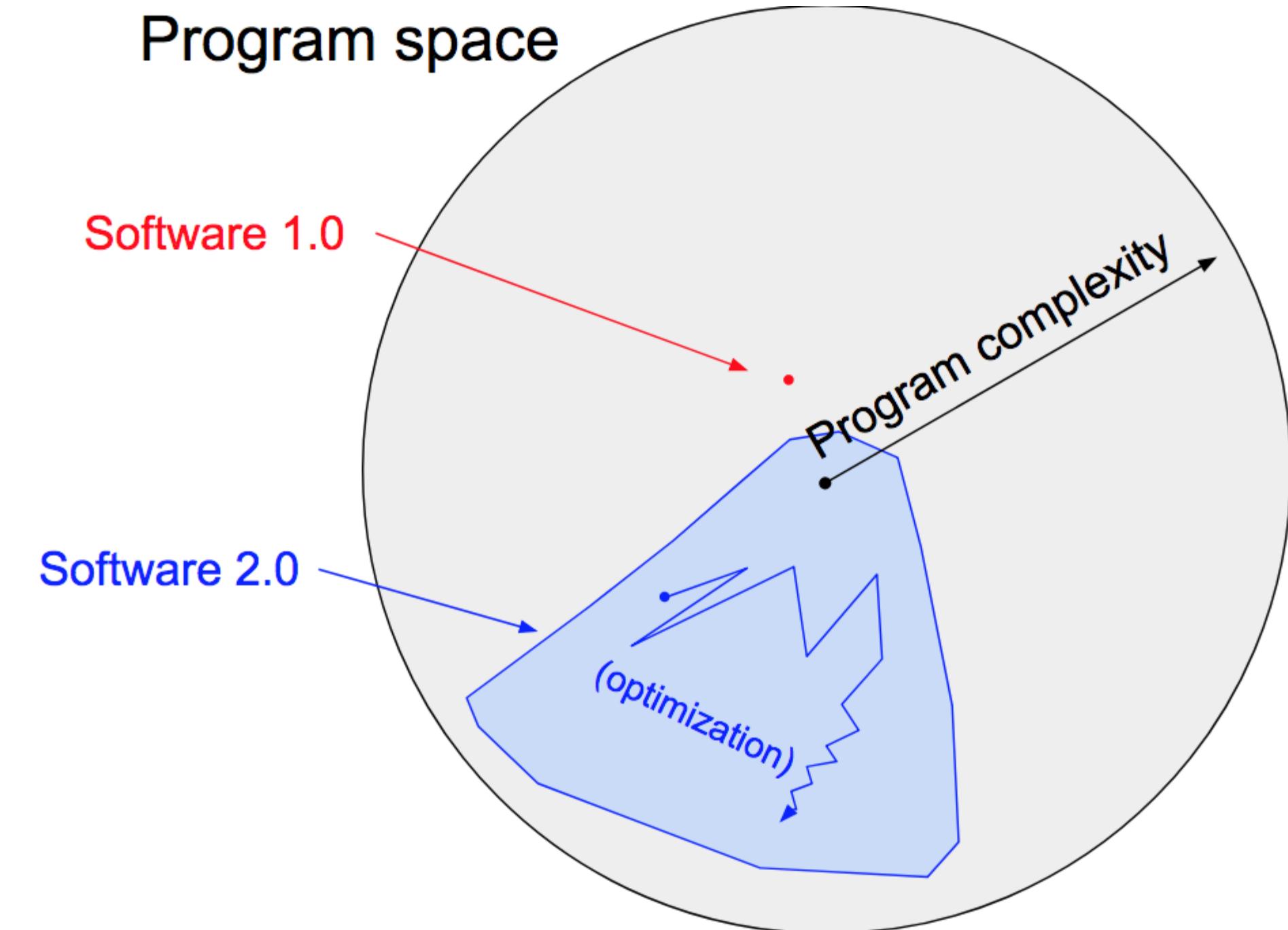
- Computationally homogeneous
- Simple to bake into silicon
- Constant running time
- Constant memory usage
- Highly portable & agile
- Modules can meld into an optimal whole
- Better than humans



**Andrej Karpathy**

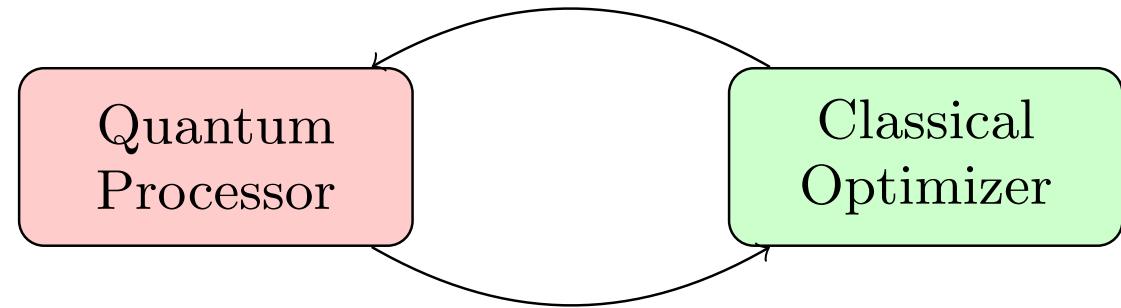
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<https://medium.com/@karpathy/software-2-0-a64152b37c35>



**Writing software 2.0 by gradient search in the program space**

# Differentiable Quantum Programming



- Variational quantum eigensolver (VQE)
- Quantum approximate optimization algorithm (QAOA)
- Quantum pattern recognition
- Quantum circuit Born machine (QCBM)

...

Quantum circuit classifier

Farhi, Neven, 1802.06002 Havlicek et al, 1804.11326

Born machine experiment

Benedetti, Garcia-Pintos, Nam, Perdomo-Ortiz, 1801.07686

TNS inspired circuit architecture

Huggins, Patel, Whaley, Stoudenmire, 1803.11537

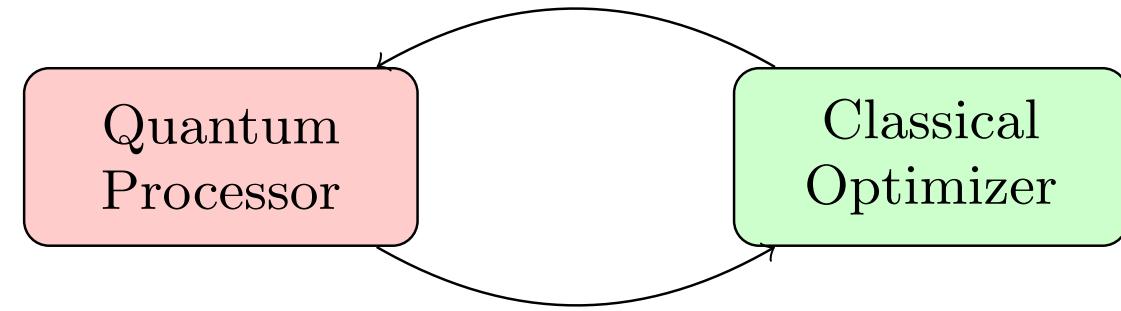
Quantum generative model

Gao, Zhang, Duan, 1711.02038

Quantum adversarial training

Dallaire-Demers, Lloyd, Benedetti 1804.08641, 1804.09139, 1806.00463

# Differentiable Quantum Programming



**It is a paradigm beyond quantum-classical hybrid**

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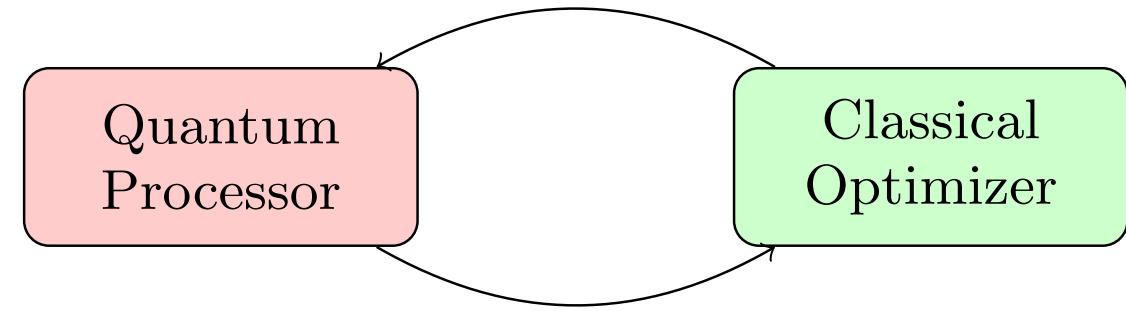
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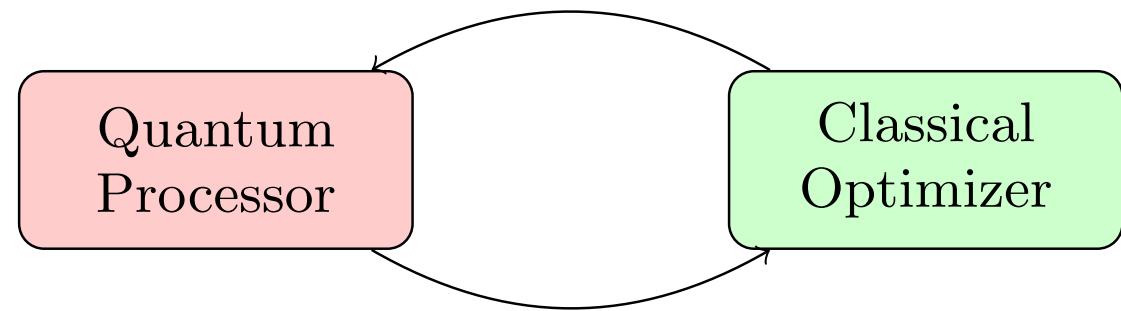
**Short term:**

What can we do with  
circuits of limited depth ?

**Long term:**

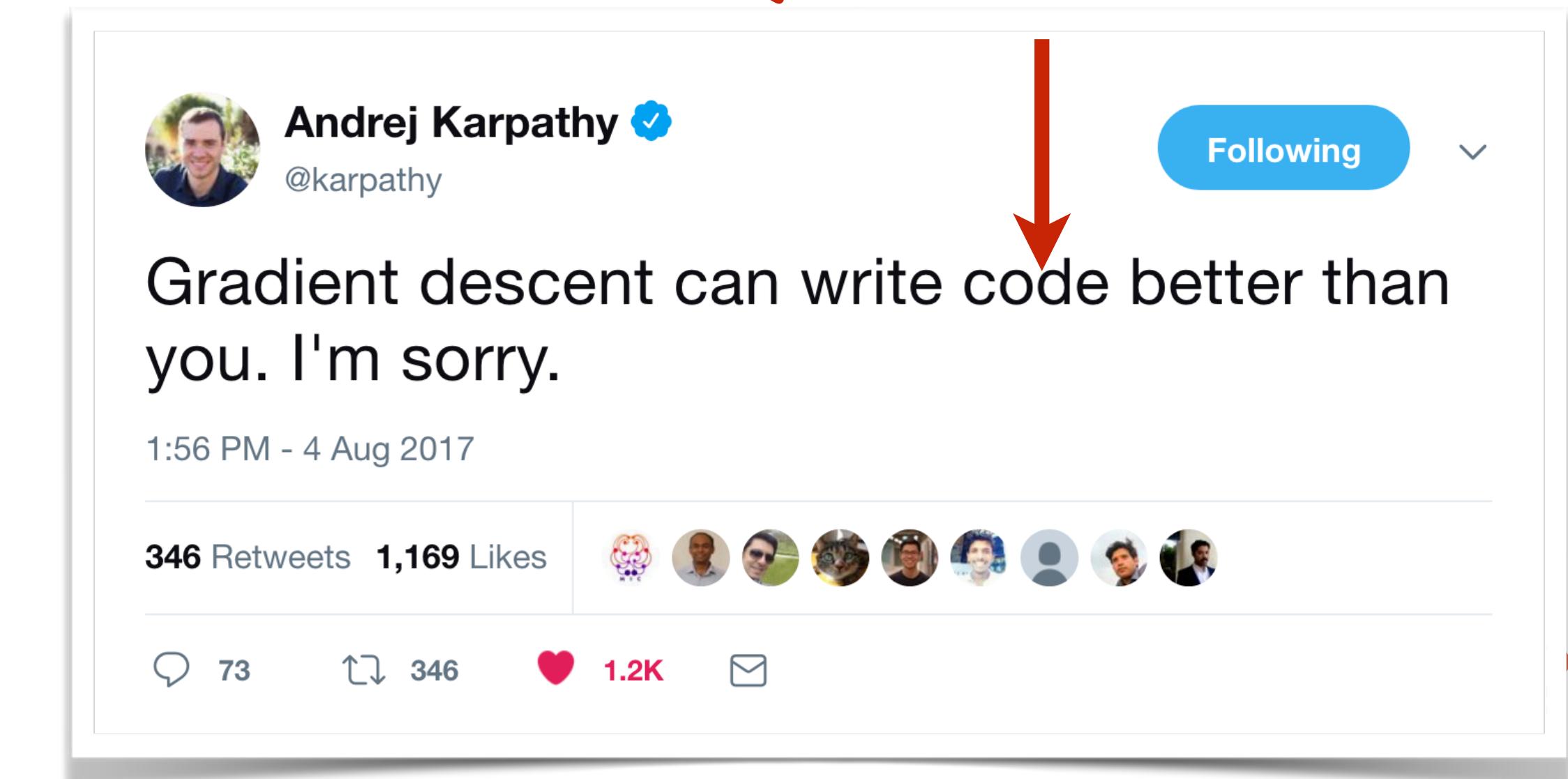
Are we really good at  
programing quantum computers ?

# Differentiable Quantum Programming



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Farhi, Neven, 1802.06002 Havlicek et al, 1804.11326

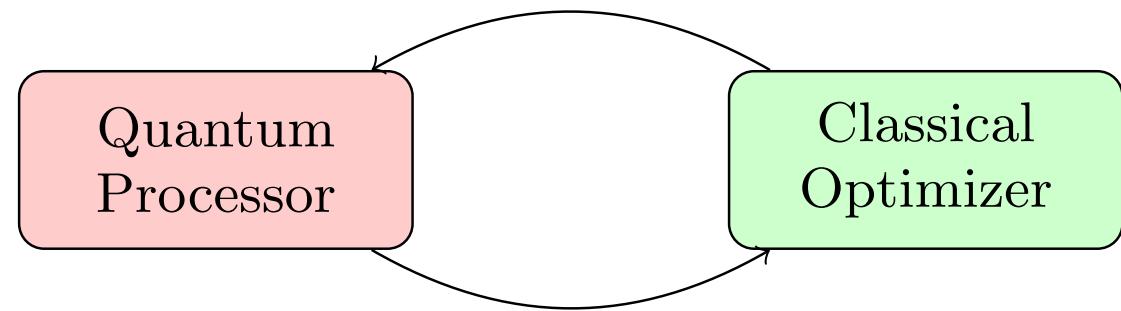
Benedetti, Garcia-Pintos, Nam, Perdomo-Ortiz, 1801.07686

Huggins, Patel, Whaley, Stoudenmire, 1803.11537

Gao, Zhang, Duan, 1711.02038

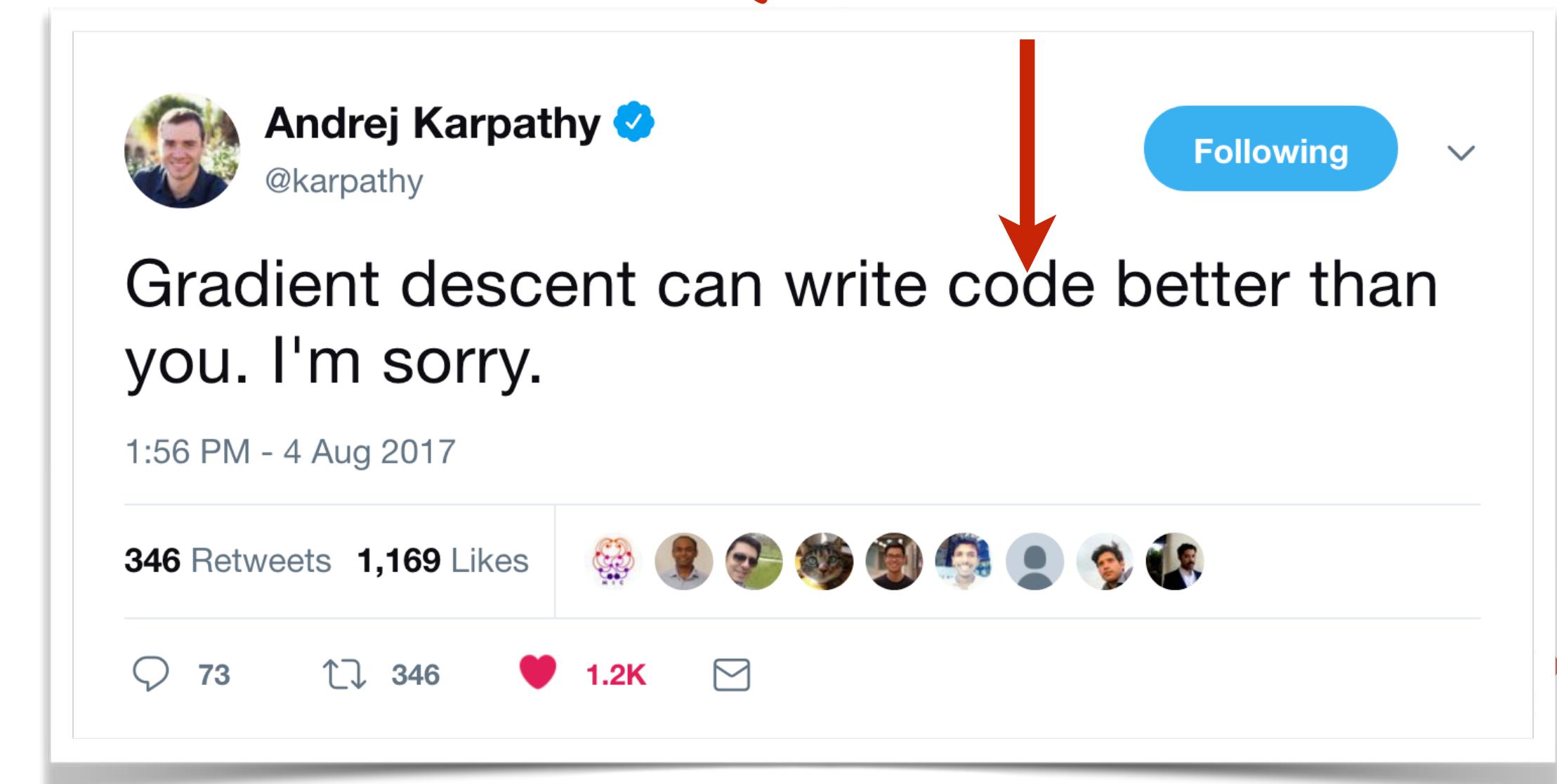
Dallaire-Demers, Lloyd, Benedetti 1804.08641, 1804.09139, 1806.00463

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Quantum ci  
Born machi  
TNS inspire  
Quantum ge  
Quantum adver

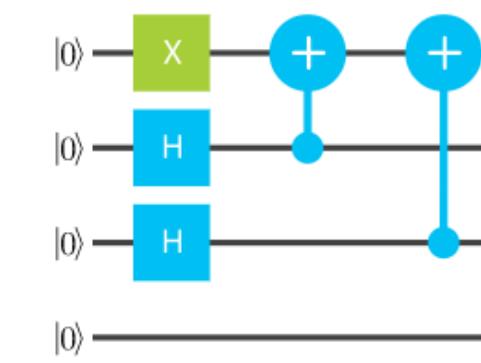
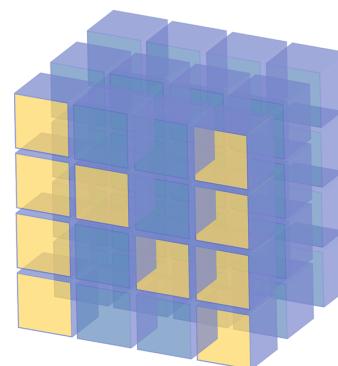
“Quantum Software 2.0”

# Try it yourself!

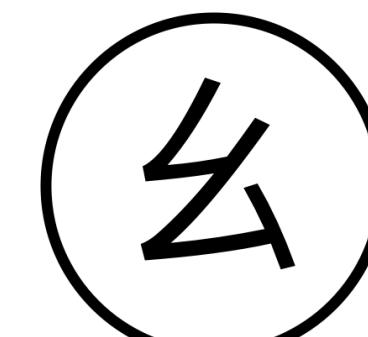
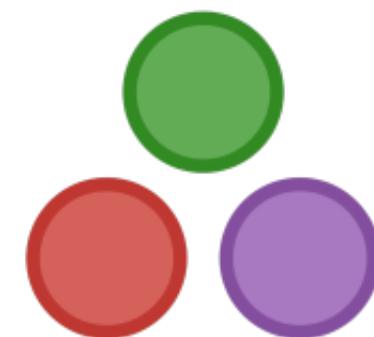


<http://lib.itp.ac.cn/html/panzhang/mps/tutorial/>

<https://github.com/wangleiphy/DL4CSRC>

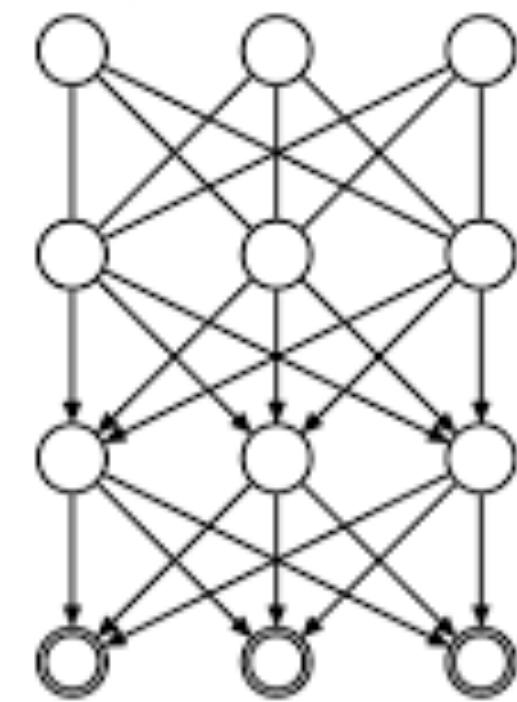


<https://github.com/GiggleLiu/QuantumCircuitBornMachine>

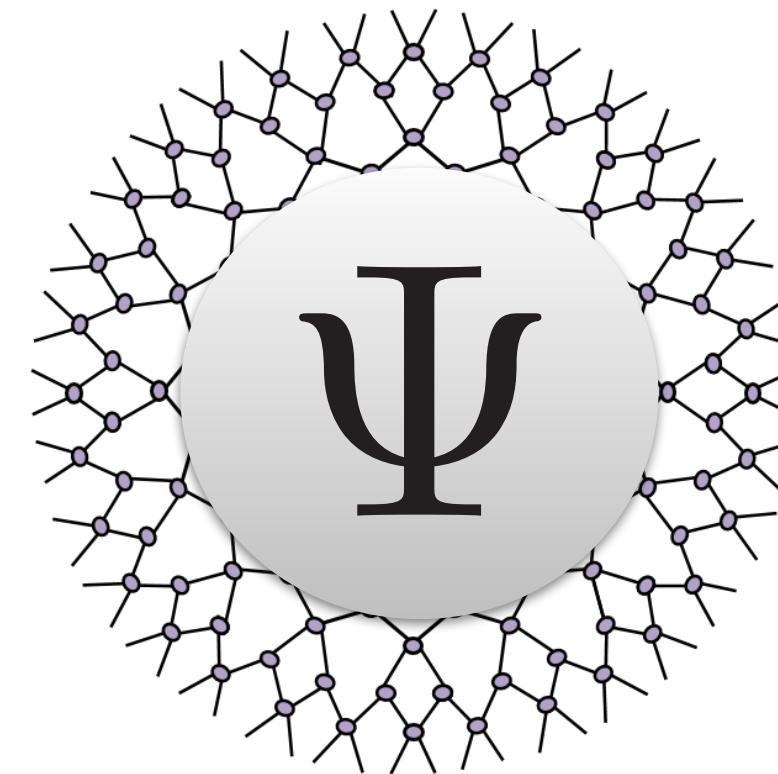


<https://github.com/QuantumBFS/Yao.jl>

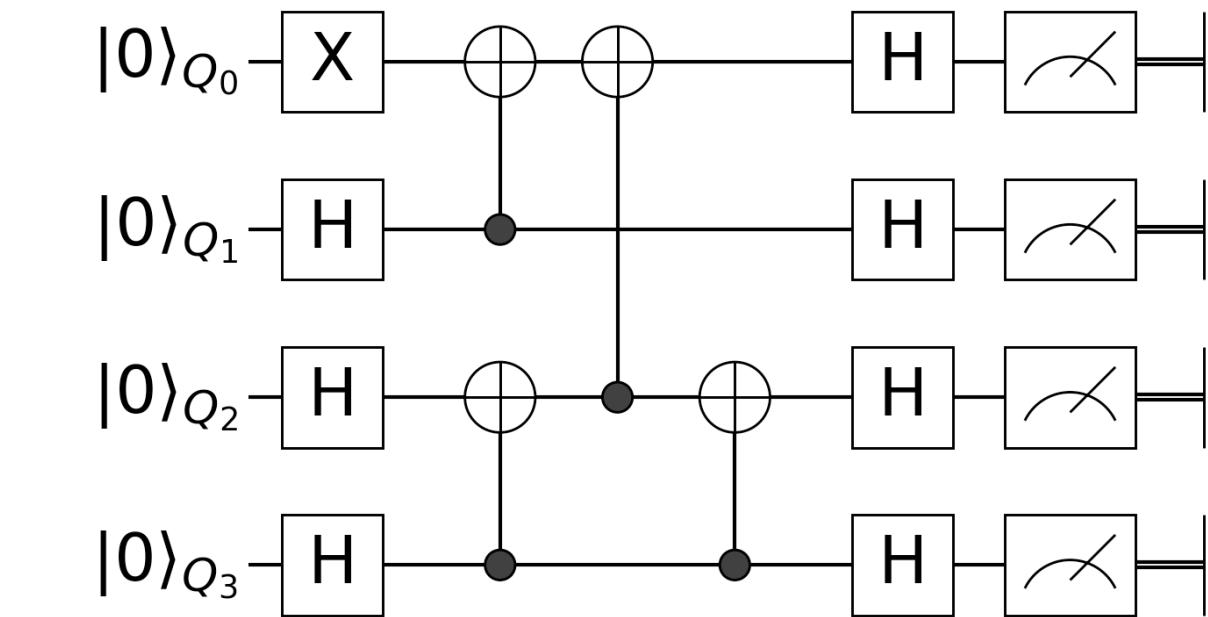
## Neural Networks



## Tensor Networks



## Quantum Circuits



“三重境界”

1. Function Approximation
2. Probabilistic Transformation
3. Information Processing Device

**Thank You!**

Pan Zhang  
Jin-Guo Liu

Jun Wang  
Zhao-Yu Han

Jinfeng Zeng  
Xiu-Zhe Luo

Song Cheng  
Tao Xiang

# 量子纠缠:从量子物质态到深度学习

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(1 中国科学院物理研究所 北京 100190)

(2 中国科学院大学 北京 100049)

2017-06-05 收到

† email: wanglei@iphy.ac.cn

DOI: 10.7693/wl20170702

## Quantum entanglement: from quantum states of matter to deep learning

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(1 Institute of Physics, Chinese Academy of Sciences, Beijing 100190, China)

(2 University of Chinese Academy of Sciences, Beijing 100049, China)

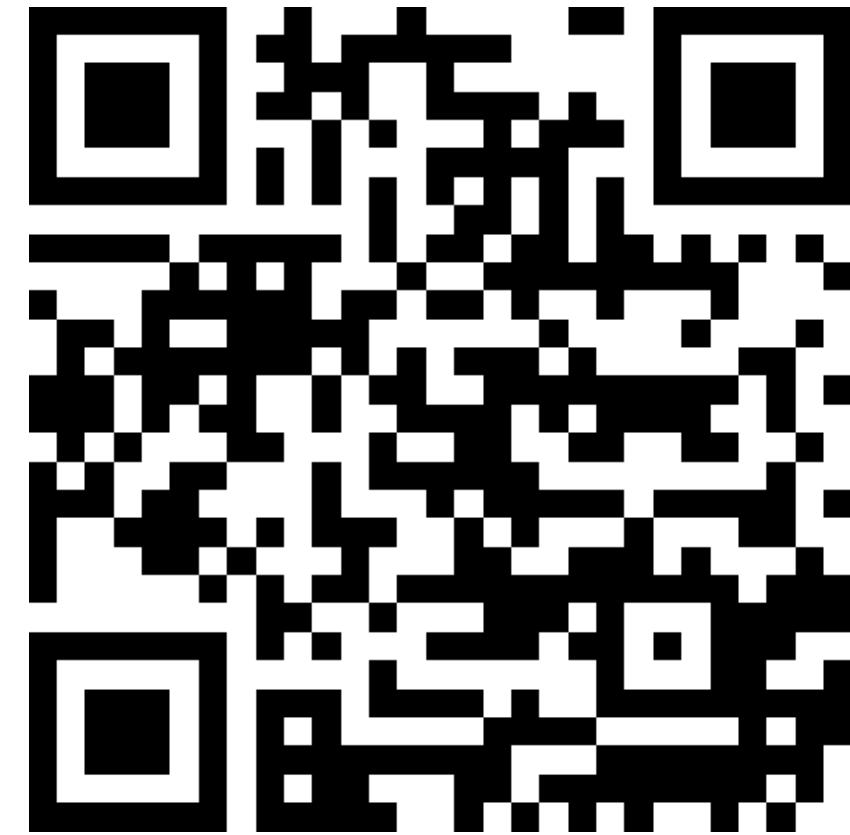


**摘要** 量子纠缠在量子物质态的研究中扮演着日趋重要的角色，它可以标记传统范式难以区分的新奇量子态和量子相变，并指导设计高效的数值算法来精确地研究量子多体问题。最近，随着一些深度学习技术在量子物理问题中的应用，人们惊奇地发现：从量子纠缠的视角审视深度学习，或许有助于反过来理解和解决一些深度学习中的问题。量子纠缠定量化地刻画了现实数据集的复杂度，并指导相应的人工神经网络结构设计。沿着这个思路，物理学家们对于量子多体问题所形成的种种洞察和理论可以以一种意想不到的方式应用在现实世界中。

《物理》杂志  
2017年7月刊

关键词

量子纠缠, 张量网络, 人工神经网络, 深度学习



[http://wangleiphy.github.io/  
lectures/DL.pdf](http://wangleiphy.github.io/lectures/DL.pdf)



Google Colab  
free GPU access

# Lecture Note on Deep Learning and Quantum Many-Body Computation

Jin-Guo Liu, Shuo-Hui Li, and Lei Wang\*

Institute of Physics, Chinese Academy of Sciences  
Beijing 100190, China

February 14, 2018

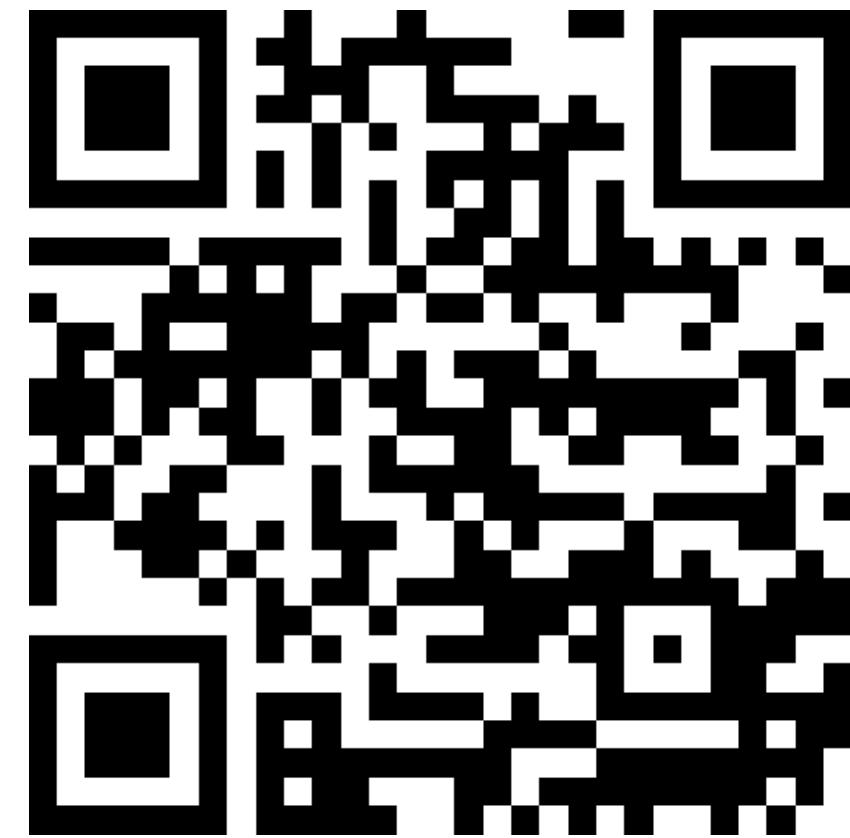
## Abstract

This note introduces deep learning from a computational quantum physicist's perspective. The focus is on deep learning's impacts to quantum many-body computation, and vice versa. The latest version of the note is at <http://wangleiphy.github.io/>. Please send comments, suggestions and corrections to the email address in below.

\* wanglei@iphy.ac.cn

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[http://wangleiphy.github.io/  
lectures/DL.pdf](http://wangleiphy.github.io/lectures/DL.pdf)



Google Colab  
free GPU access

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# Catch up with latest updates

The screenshot shows the homepage of the Kavli Institute for Theoretical Physics (KITP) at UC Santa Barbara. The main navigation bar includes links for HOME, DIRECTORY, ACTIVITIES, PROPOSE ACTIVITY, APPLY, FOR VISITORS, TALKS ARCHIVE, and OUTREACH. A featured program is "Machine Learning for Quantum Many-Body Physics", coordinated by Roger Melko, Amnon Shashua, Miles Stoudenmire, and Matthias Troyer, with scientific advisors Juan Carrasquilla, Pankaj Mehta, Lei Wang, and Lenka Zdeborova. The program's purpose is to bring together experts from physics and computer science to discuss machine learning applications in many-body physics. It includes sections for DATES (Jan 28, 2019 - Mar 22, 2019), INFORMATION, and an Apply button.

The screenshot shows the homepage of the American Physical Society (APS) March Meeting 2019 in Boston, MA. The meeting dates are March 4-8, 2019. The navigation bar includes links for Publications, Meetings & Events, Programs, Membership, Policy & Advocacy, Careers In Physics, Newsroom, and About. The APS physics logo is prominently displayed. A sidebar on the right provides social media links for Facebook, Twitter, and more.

**KITP, Santa Barbara Program  
ML for Quantum Many-Body Physics  
Jan 28-Mar 22, 2019**

**APS March meeting focus session  
ML in Condensed Matter Physics  
Boston, Mar 4-8, 2019**